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Cortical mechanisms of perceptual learning

Andrea Bertana, Ruben van Bergen, Koen Haak,
Sam Ling, Janneke Jehee

Radboud University Radboudumc

Which of the two roads has black ice?

Now?

Feature: shininess, color

With training, the brain can improve its ability to extract features that are relevant for a perceptual task (**perceptual learning**)

e.g. Fiorentini & Berardi, Nature 1980; Crist et al., J. Neurophys. 1997; Ahissar & Hochstein, Nature,1997; Dosher & Lu, Vision Res 1999; Li et al., Nat. Neurosci, 2004.

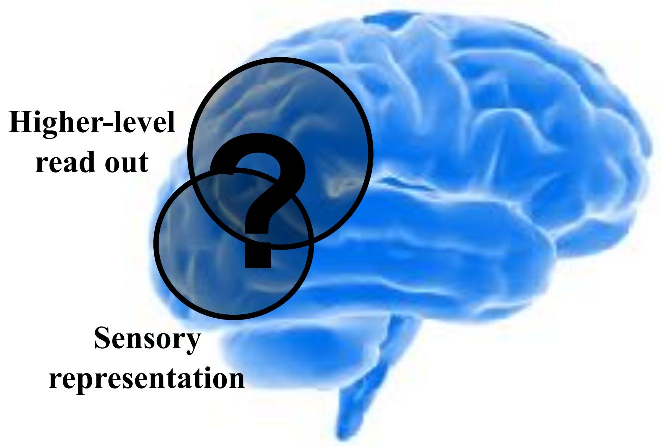
What are the mechanism of visual perceptual learning ?

Current theories:

- Learning refines the sensory (low-level) representation of behaviorally relevant information (e.g., Crist et al, Nat. Neurosc., 2001; Furmanky et al., Curr.Biol., 2004; Schoups et al., Nature, 2011; Jehee et al. J.Neurosci, 2012;)

- Learning involves improvements in how the sensory representation is read out by higher-level decision areas (e.g. Dosher & Lu,Vision Research, 1999; Law & Gold, Nat. Neurosc., 2008)

Can we somehow reconcile these findings?



Reconciling findings: learning improves sampling efficiency…

Previous behavioral work: Observers use only part of the stimulus in decision-making

(e.g., Dakin, J.Opt.Soc.America, 2001)

Behavioral decision window

Post-learning: *larger* window

Learning increases the efficiency with which observers sample from a stimulus in order to make a decision (Li et al., Nat Neurosci, 2004, Kurki & Eckstein, J.Vision, 2014; Moerel, Ling & Jehee, J.Vision, in press)

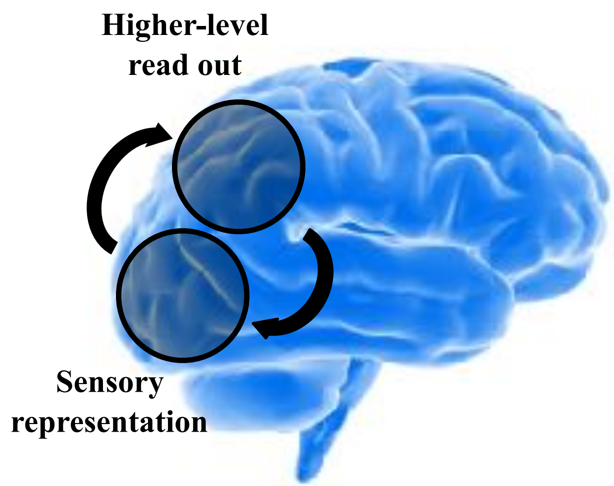
Our hypothesis: post-training changes in behavioral decision template are linked to top-down attention

Predictions:

1. Training shapes attentional processes in higher-level areas, such that the attentional spotlight on early visual cortex grows larger

2. As a consequence, the low-level representation of the stimulus will improve *(low-level refinement)*

3. And it will become easier for high-level decision areas to select the relevant information *(more efficient read-out)*



Possible outcomes*:

1. **Learning does not induce any change**
   (no learning effects in neither low and nor high level visual regions)

2. **Learning improves the sensory representation of the stimulus only**
   (*learning effects in low-level regions only*)

    1. Is it linked to top-down attention ?
    2. Is it spatially specific (i.e. tied to the behavioral decision template)?

3. **Learning improves the read-out of the sensory information only**
   (more effective read-out, learning effects in higher-level regions only)

    1. Is it linked to top-down attention ?

4. **Learning improves both the sensory representation of the stimulus and higher-level read-out of this information** (*learning effects in both regions*)

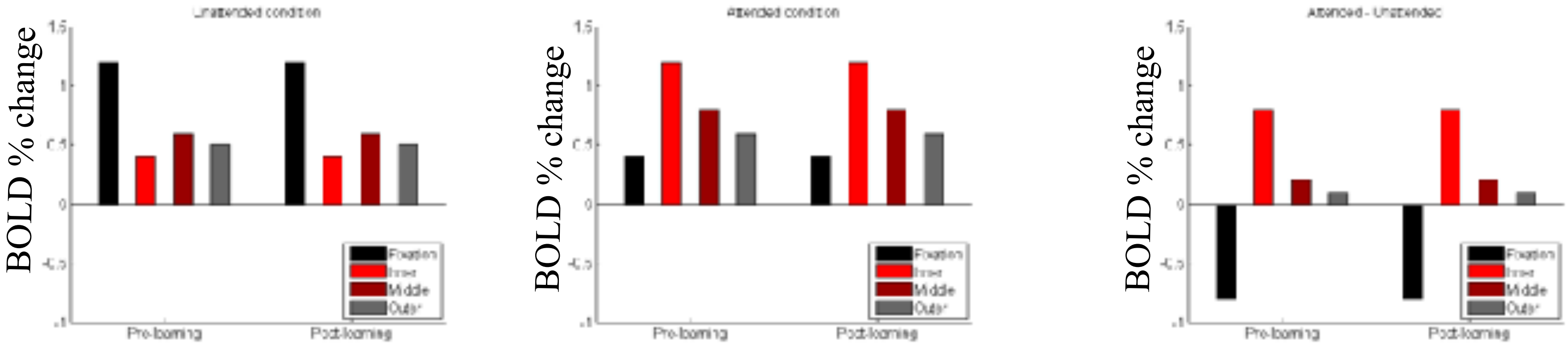
    1. Is it linked to top-down attention ?
    2. Is it spatially specific (i.e. tied to the behavioral decision template)?

* Each of the following outcomes assumes that we will be able to observe **attentional modulations** in both low-level and higher-level regions in both pre and post learning stages (namely that we observe an overall BOLD increase in the ATTENDED condition respect to UNATTENDED condition).

1. **Learning does not induce any change**

   (no learning effects in both low and high level visual regions)

   Main effect of attention, no effect of learning



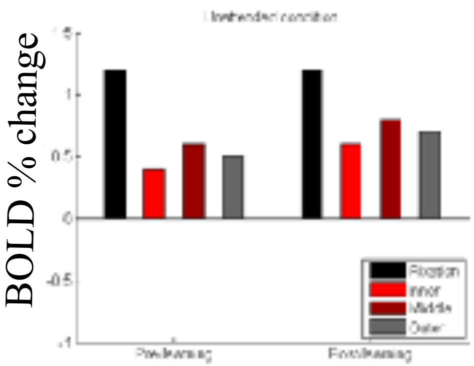
No BOLD changes Pre vs Post learning for all conditions

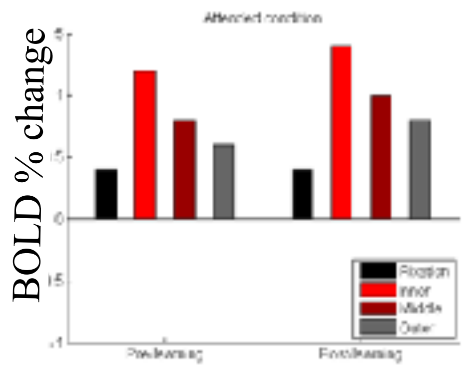
2. Learning improves the sensory representation of the stimulus only
(*learning affects only low-level regions*)

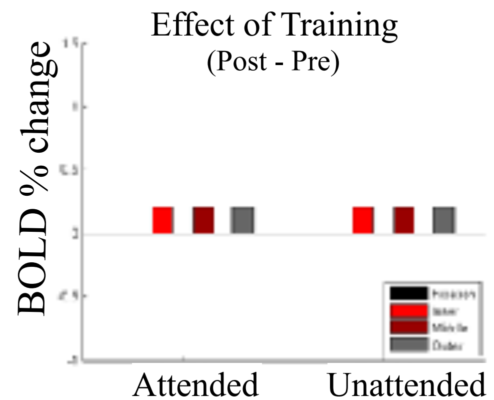
Main effect of attention, Main effect of training

Two possibilities:

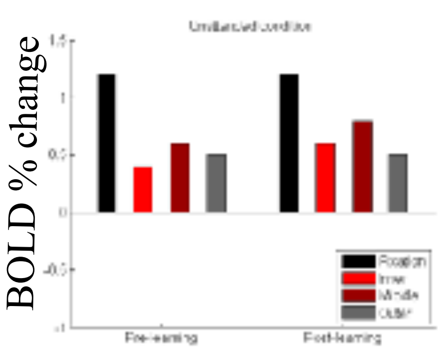
- It is NOT spatially specific

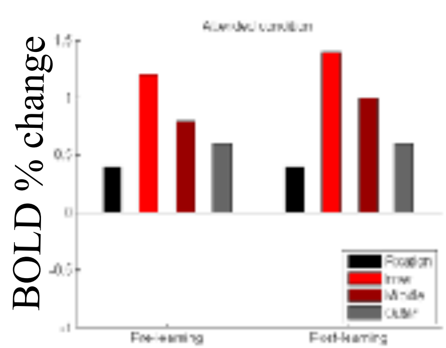


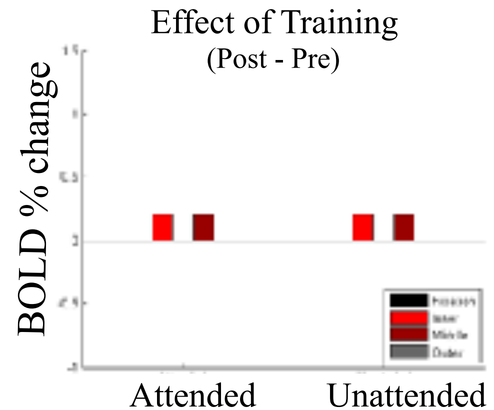




- It IS spatially specific



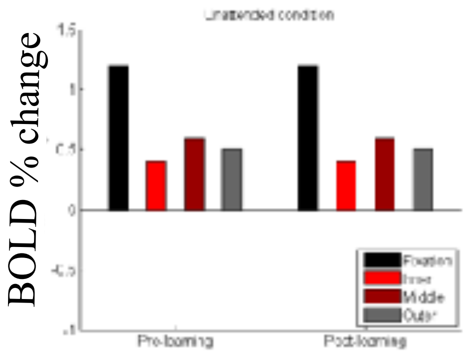


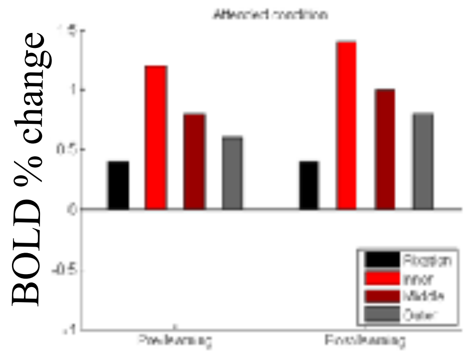


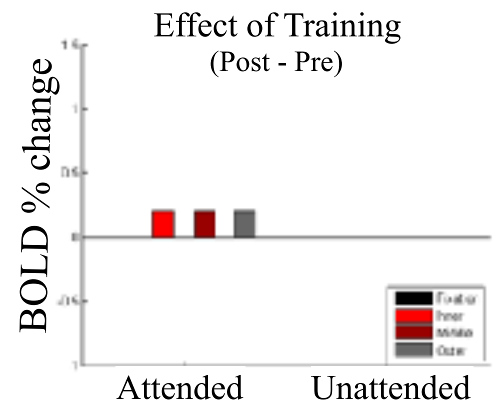
2. Learning improves the sensory representation of the stimulus only
(*learning affects only low-level regions*)

Interaction effect attention and training:

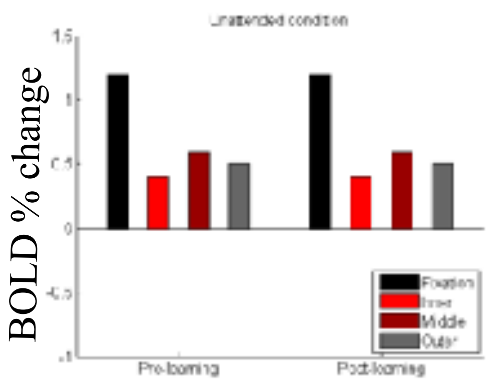
1. Learning is linked to top-down attention, but is not spatially specific

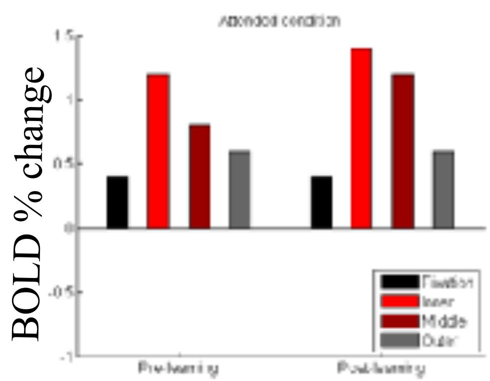


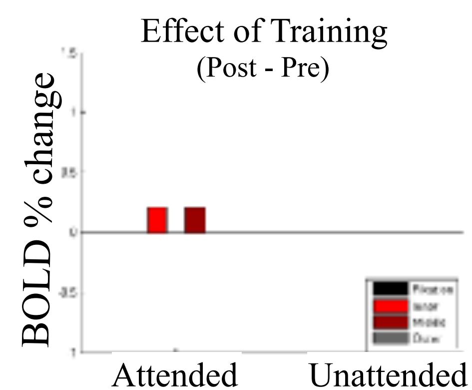




2. Learning is linked to top-down attention, and is also spatially specific







The previous examples are valid also for:

3. **Learning improves the read out of the sensory information only**
   (more-effective read-out, learning effects in both regions)

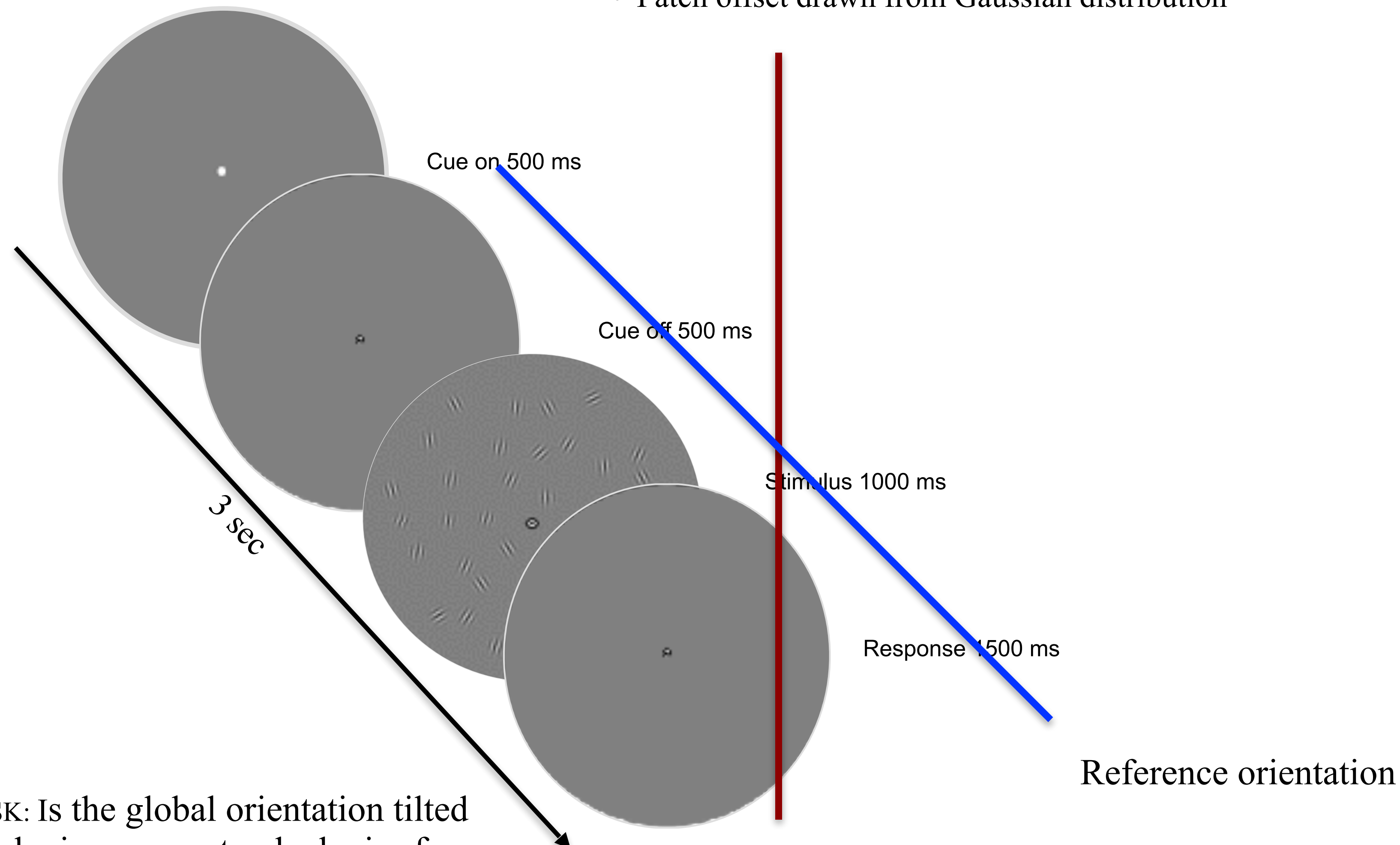
   Training-based effects in higher-level visual cortex ONLY and NOT in lower-level visual cortex.

4. **Learning improves both the sensory representation of the stimulus and the read out of this information** (*learning effects in both areas*)

   If we observe all these changes in both higher and lower-level visual regions

Task

- Global orientation
- Patch offset drawn from Gaussian distribution



TASK: Is the global orientation tilted clockwise or counterclockwise from the reference orientation ?

Procedure

Pre - Training	Training	Post - Training
Behavioral *3 days / 1800 Trials*	*10 days / > 6000 Trials*	Behavioral *3 days / 1800 Trials*

> 18 days

Behavioral:

Goal: to measure orientation discrimination threshold and behavioral decision template

−Two reference orientations (45° & 135°)

−900 trials per orientation

This replicates our previous set-up
(Moerel et al, J.Vis, 2016)

Procedure

Pre - Training	Training	Post - Training
Behavioral *3 days / 1800 Trials*	*10 days / > 6000 Trials*	Behavioral *3 days / 1800 Trials*

$\underbrace{\hspace{6em}}_{> 18 \text{ days}}$

> 18 days

Training:

–One reference orientation only

–Auditory feedback on wrong trials

–600 trials per day; >6000 trials total

This replicates our previous set-up
(Moerel et al, J.Vis, 2016)

Procedure

Pre - Training	Training	Post - Training
fMRI *1 day* / Behavioral *3 days / 1800 Trials*	*10 days / > 6000 Trials*	fMRI *1 day* / Behavioral *3 days / 1800 Trials*

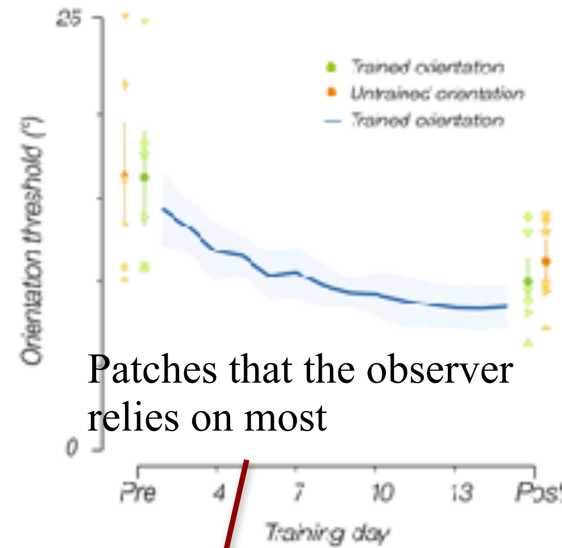
> 18 days

fMRI:

- 2 conditions (counterbalanced)
  - ATTENDED (orientation discrimination task)
  - UNATTENDED (fixation task)
- Block design
- 4 Trials per block
- 2 reference orientations (45° & 135°)

Data Analysis - Behavioral

- Psychophysics (Replicating Moerel et al. J.Vis, 2016)
    - Behavioral orientation discrimination threshold
    - Reverse correlation to obtain behavioral decision templates

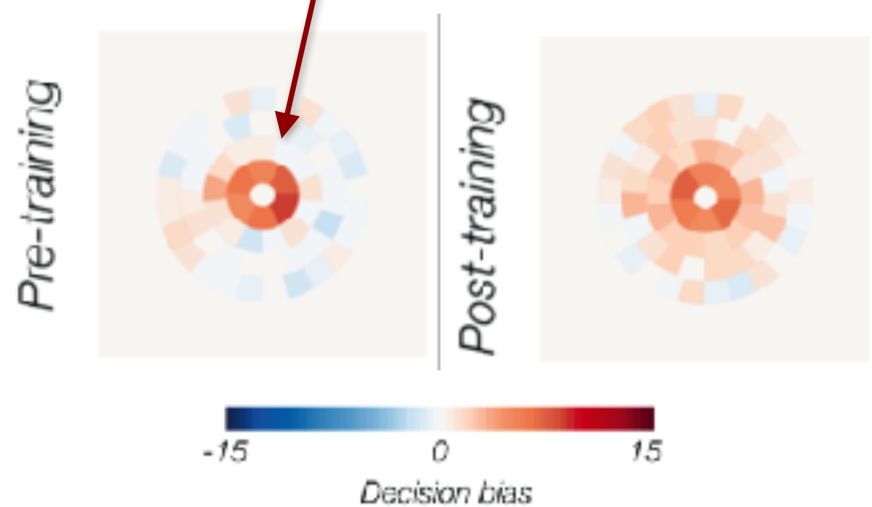


Patches that the observer relies on most

Behavioral responses

Correlate behavioral responses with noisy images
(reverse correlation)

Behavioral decision template



Data Analysis

Example of a psychometric function (S02), across conditions

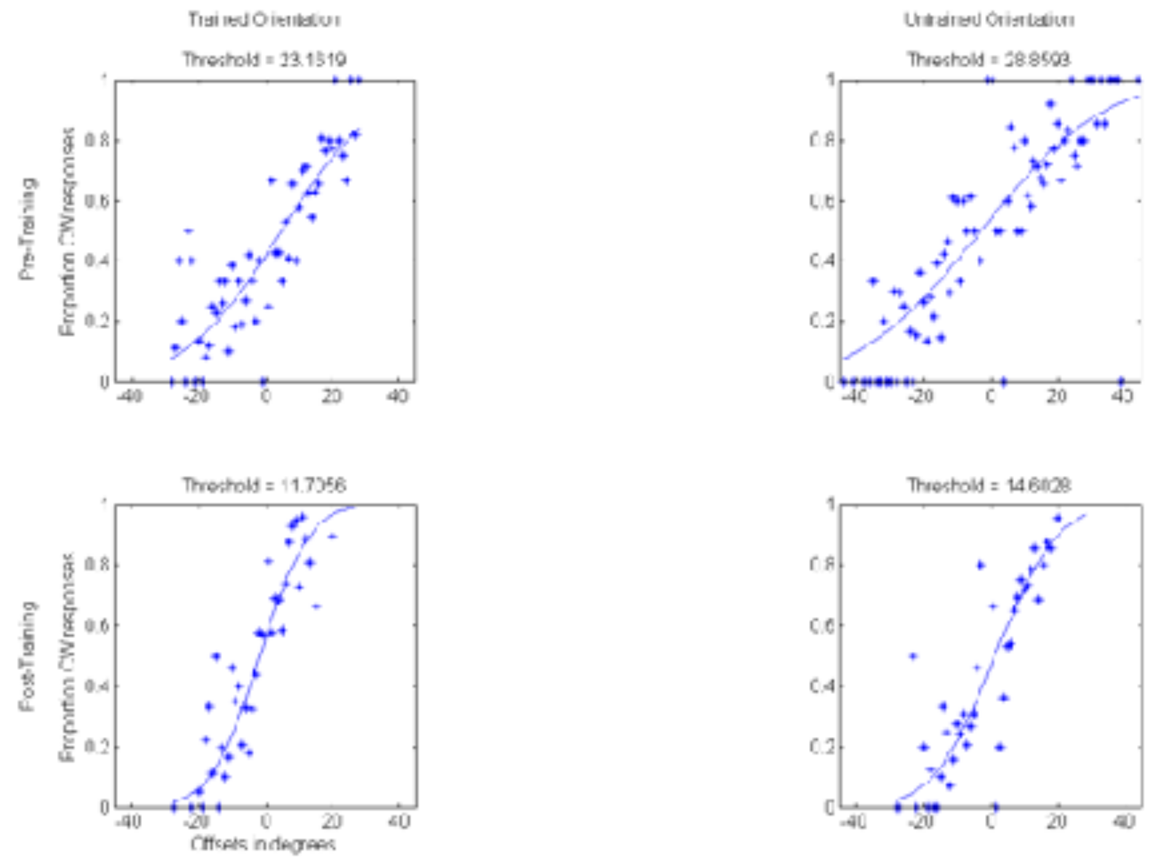


Figure. Each data point combines the set of responses given one orientation offset. The line shows the cumulative Gaussian fitted to the data, using maximum likelihood. The standard deviation of this fitted function was taken as the subject's orientation discrimination threshold.

Data Analysis- Individual subjects (S01)

Figure 1

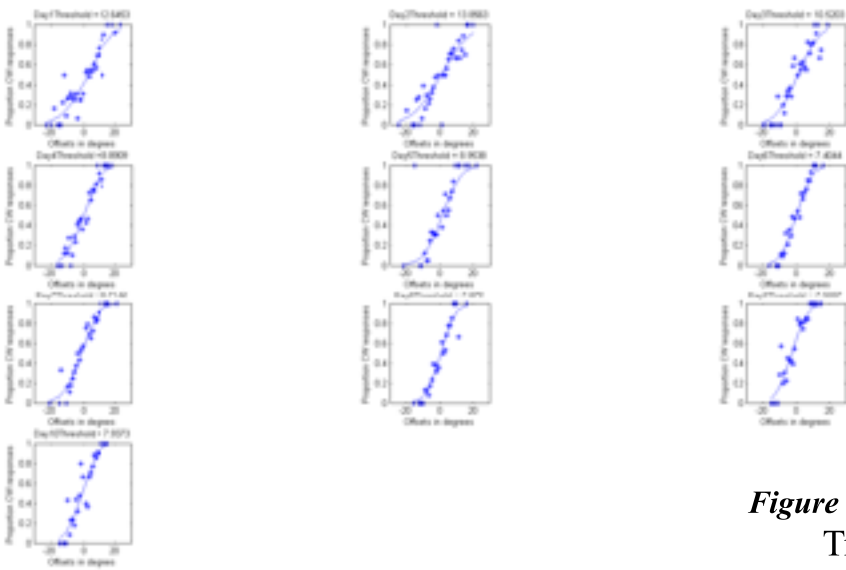


Figure 2

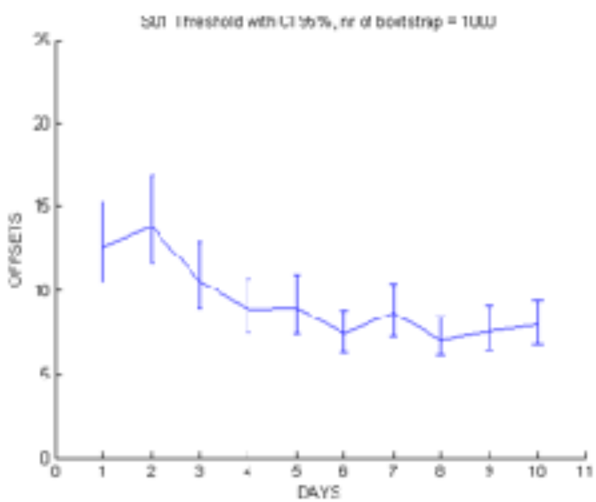


Figure 3

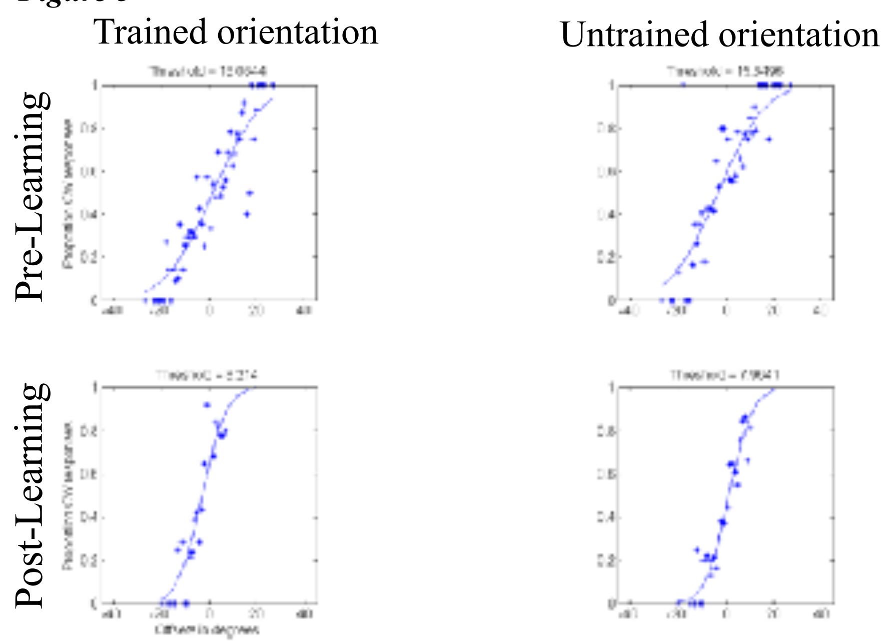


Figure 1. Psychometric functions for each day of training.

Figure 2. Subject’s threshold over time. The error bars represent the 95% CI after 1000 bootstraps.

Figure 3. Psychometric functions across conditions, as obtained in the pre- and post-training thresholding sessions.

Data Analysis- Individual subjects (S02)

***Figure** 1*

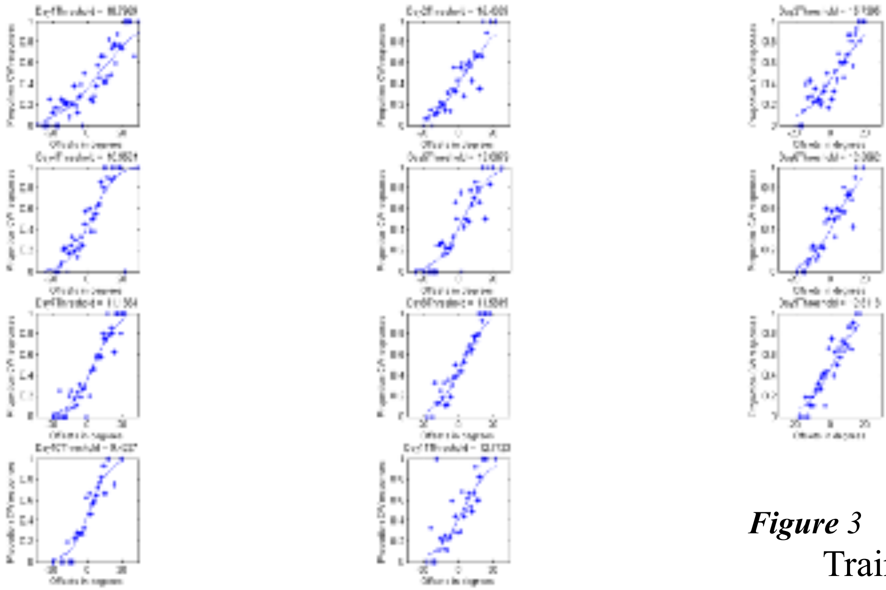


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***Figure** 2*

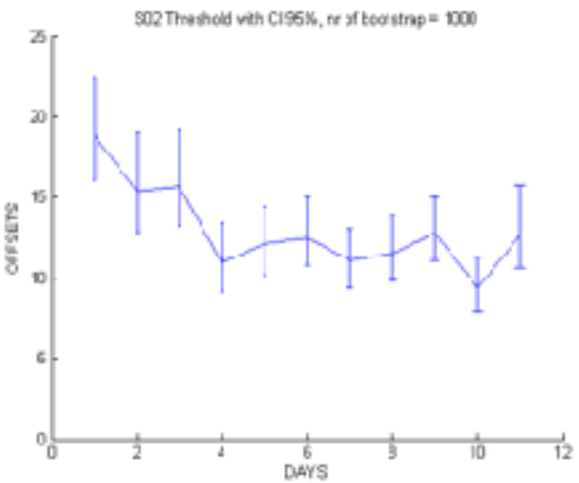
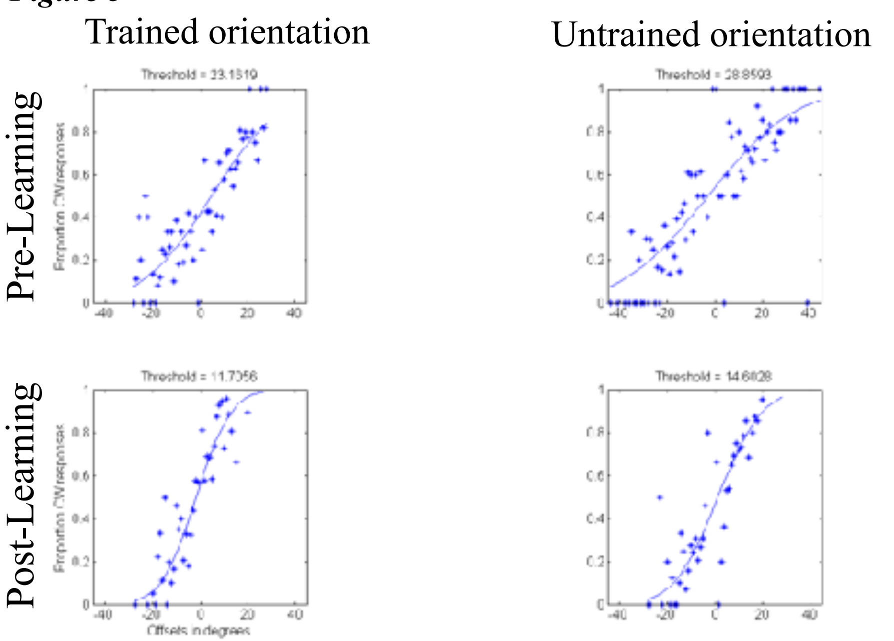


***Figure** 3*



Data Analysis- Individual subjects (S03)

Figure 1

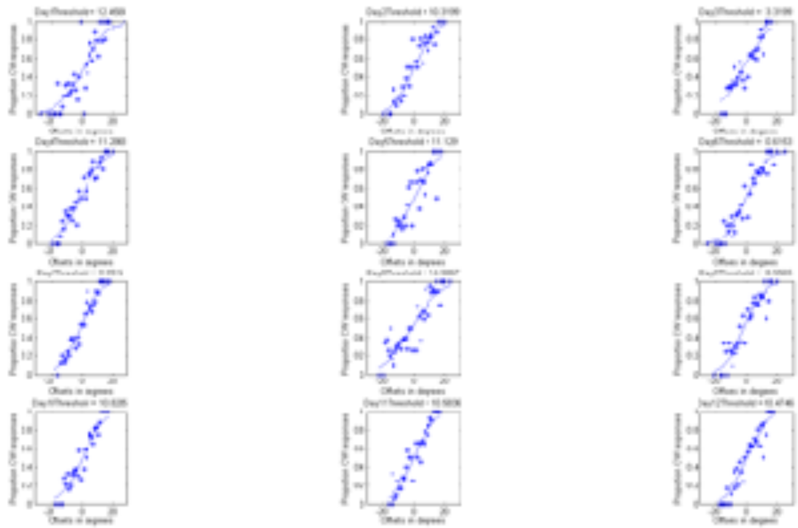


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Figure 2

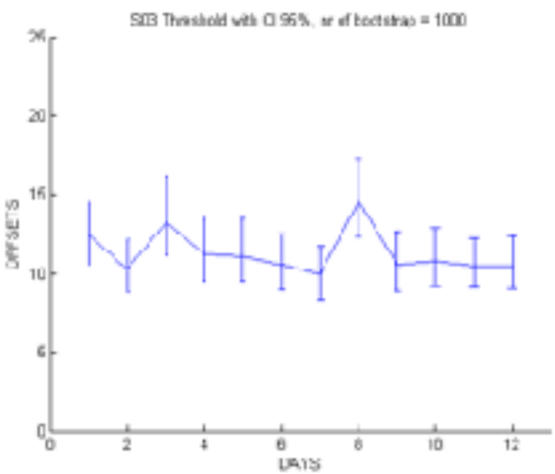
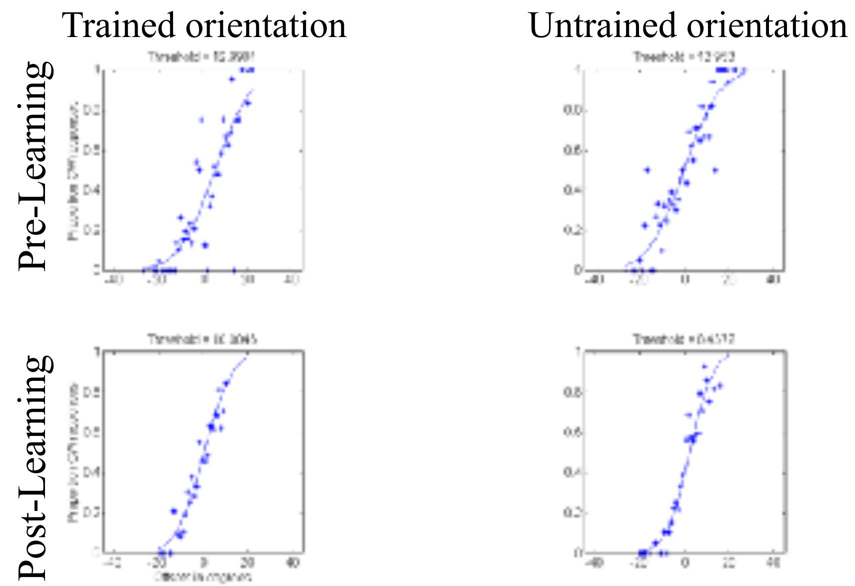
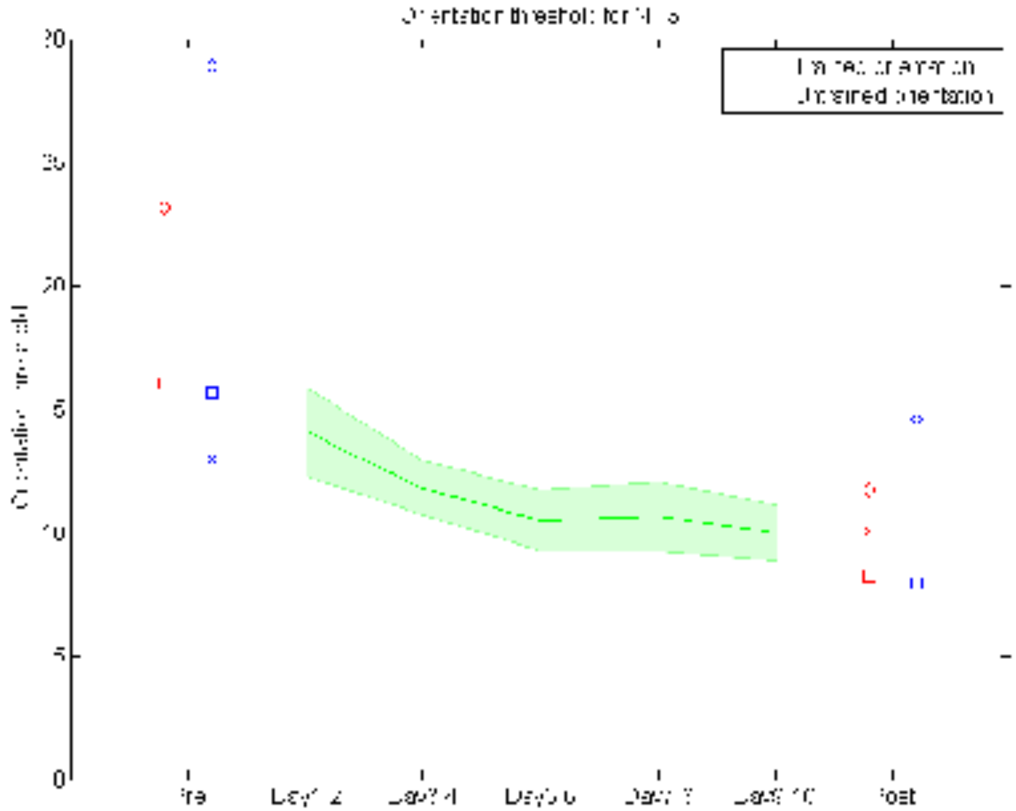


Figure 3



Data Analysis

Behavioral orientation discrimination threshold over time, mean across subjects (n = 3)



Now that we added the '
across subjects (n=3)' in
title, there is no need to
change it in the plot right

Figure. Orientation discrimination thresholds over time, averaged across observers. Different symbols represents different subjects. The shaded area correspond to ± 1 SEM.

Data Analysis

Behavioral decision templates averaged across subjects (n = 3)
(obtained using reverse correlation)

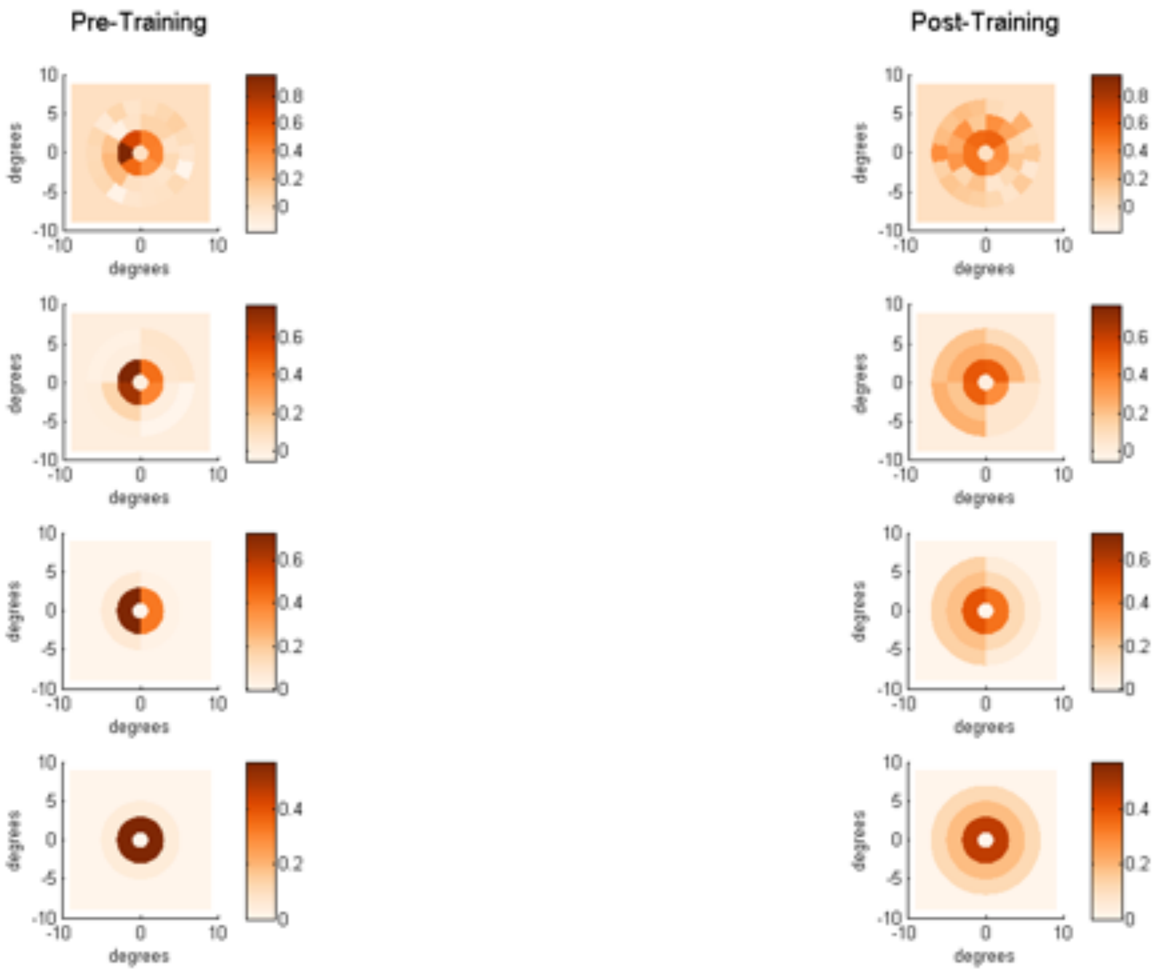


Figure. Data from the pre and post training thresholding sessions are used here. All orientations have been collapsed to the left orientation. N = 3.

Data Analysis:

Reverse correlation *(logistic regression)*

Goal*: estimate the degree to which each gabor contributes to the observer's behavioral template*

The variables we have are:

- r_i = The subject's response on a given trial *i*. The responses are binary: 1 = CW, 2 = CCW.
- x_{ij} = The orientation of gabor *j* on trial *i*. The orientations are defined as the offsets with respect to the mean orientation.

Formula of logistic regression:

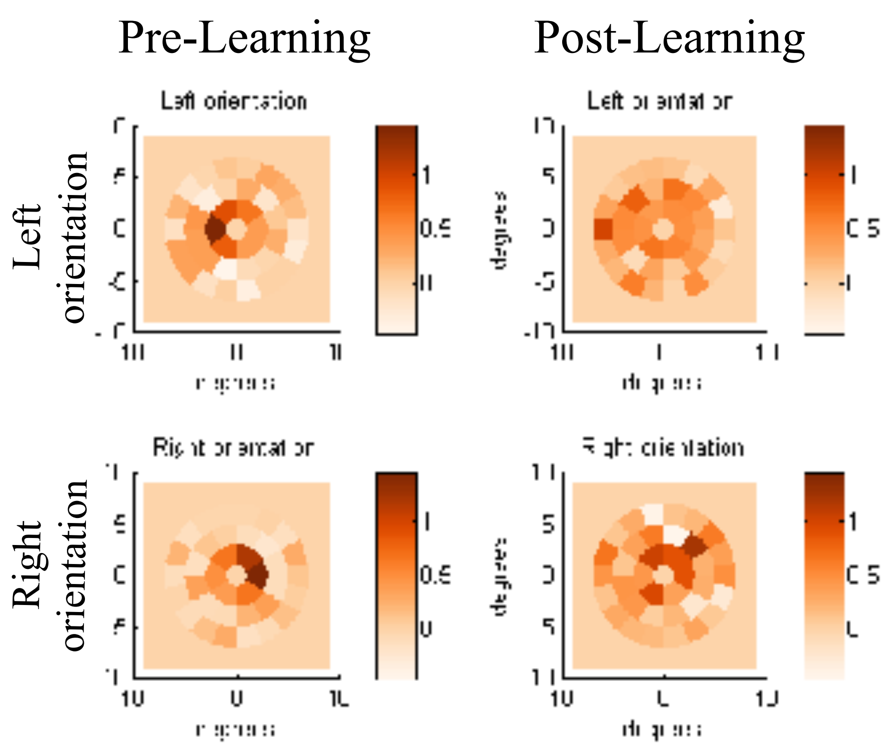
$$p(r_i = 1|x_i) = 1/1 + e^{-wx_i}$$

Meaning, the probability of CW response on trial *i*, given the sets of orientations $\mathbf{x_i}$, is a function of these orientations multiplied by some weights *w* (and normalised, so that we get probabilities that are between 0 - 1).

↓

We need only to estimate the sets of weights *w* that best predict **r**.
(In practical terms we use *mnrfit* on Matlab.)

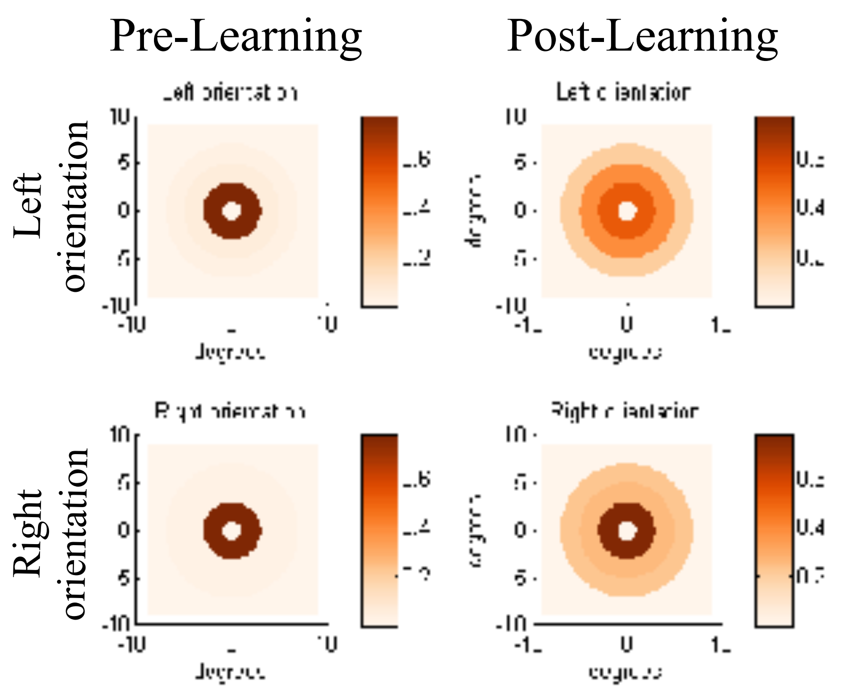
Data Analysis - individual subjects (S01)



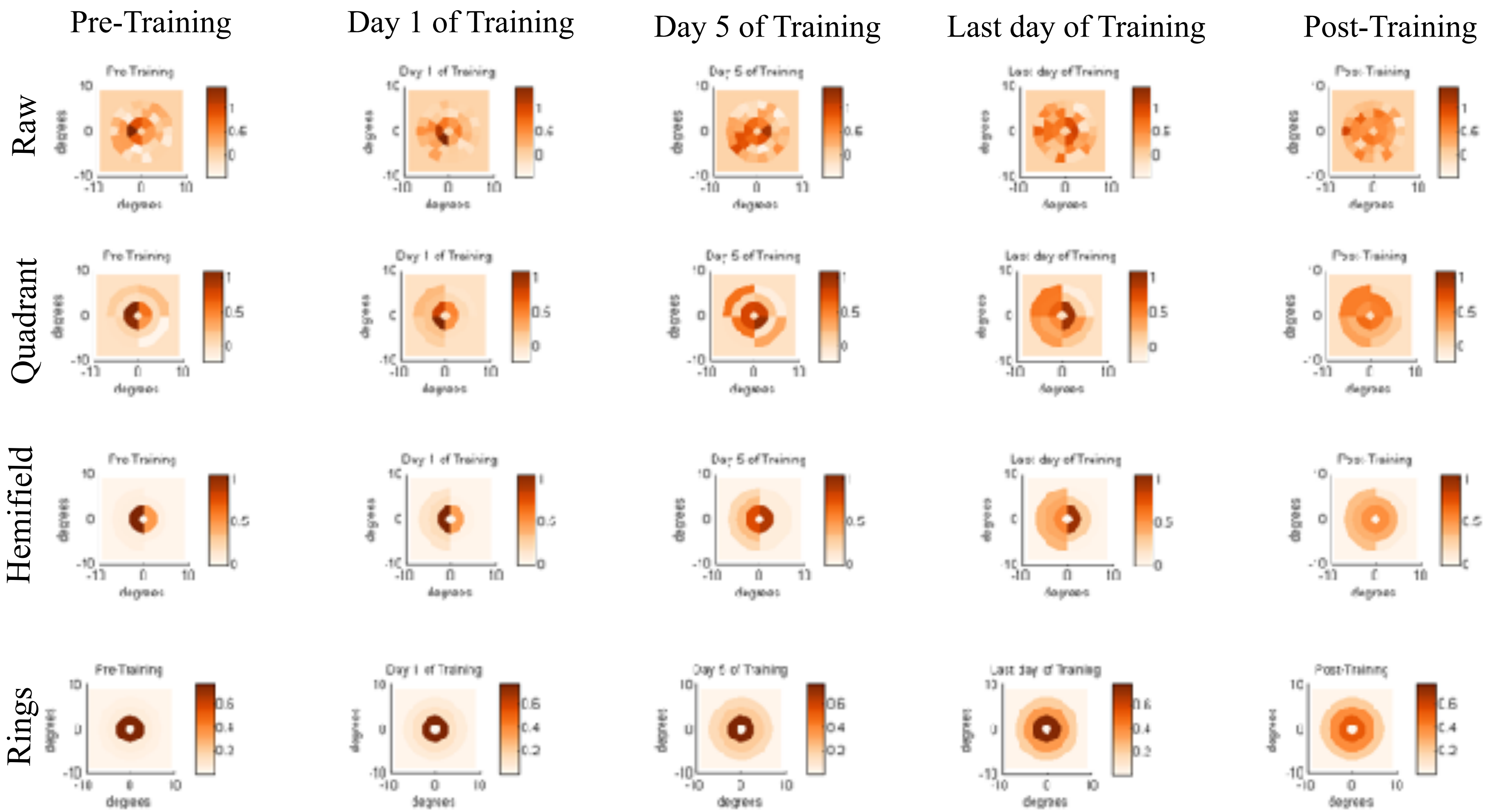
Figures. Training based improvements in decision templates. Here for both orientations. S01 trained on the left orientation.

Upper left figure. Raw data

Lower right figure. Each ring show the mean across all patches of similar eccentricity values (i.e. rings).

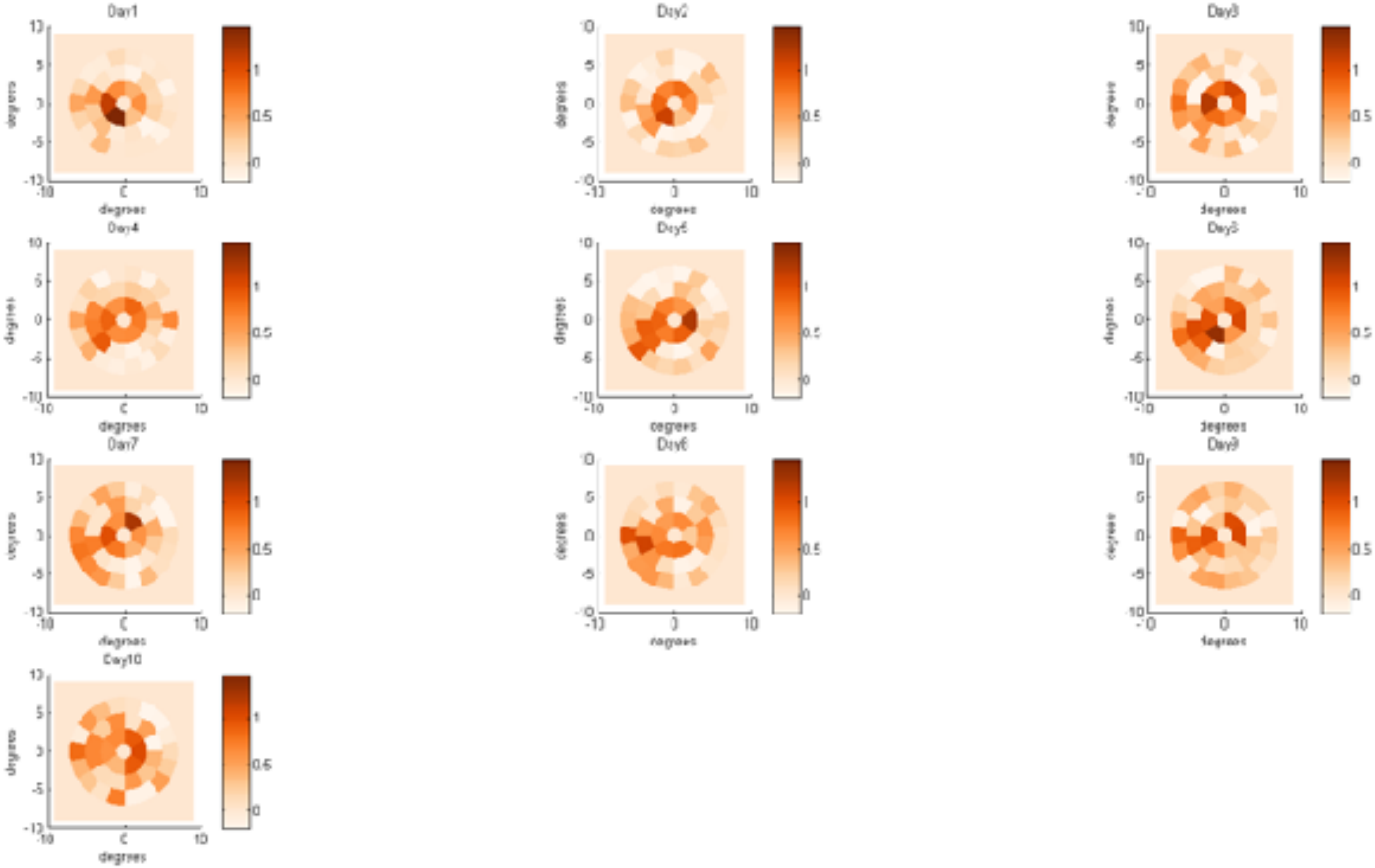


Data Analysis - individual subjects (S01)



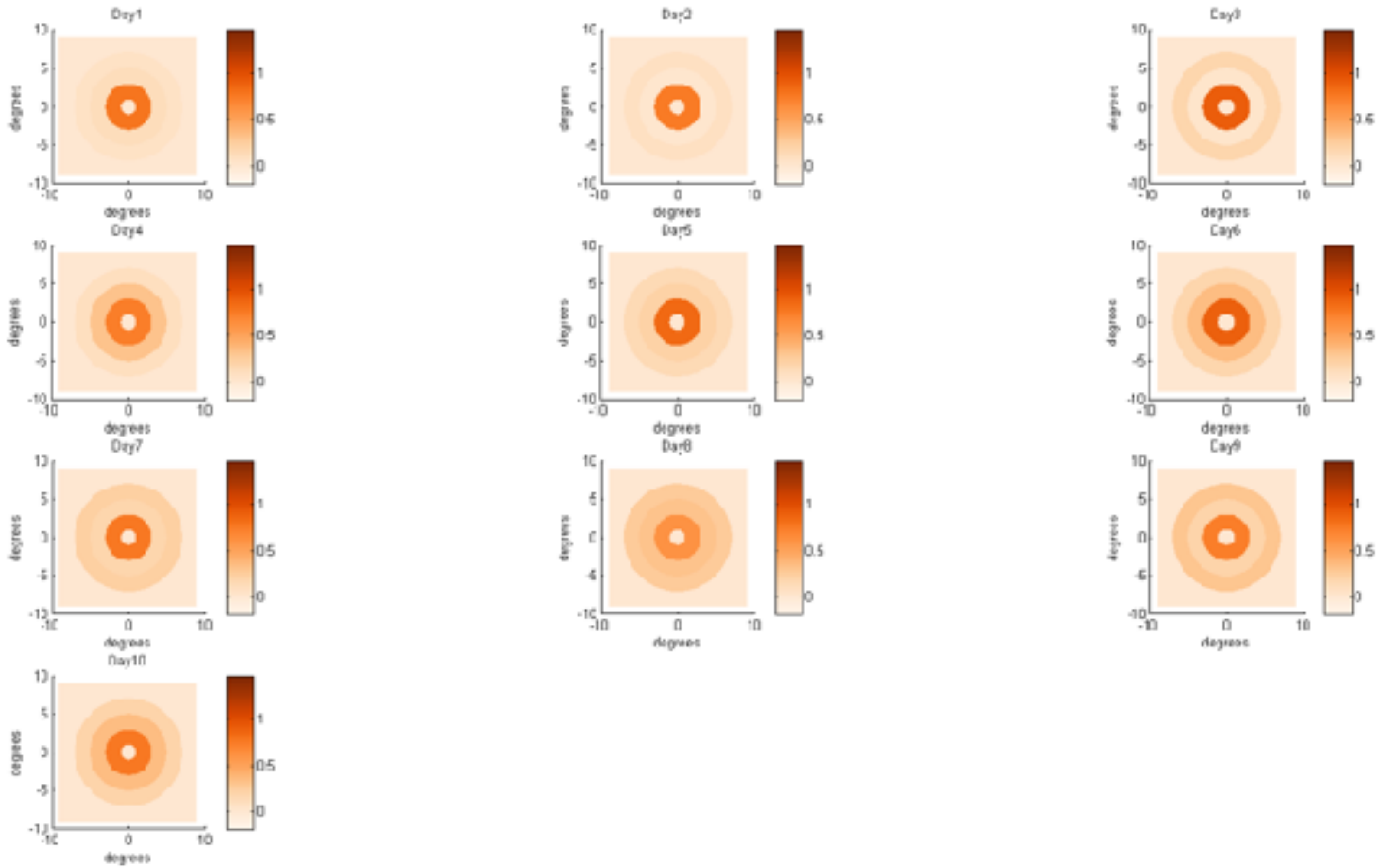
Figure; Behavioural decision templates over time. Raw data values.

Data Analysis - individual subjects (S01)



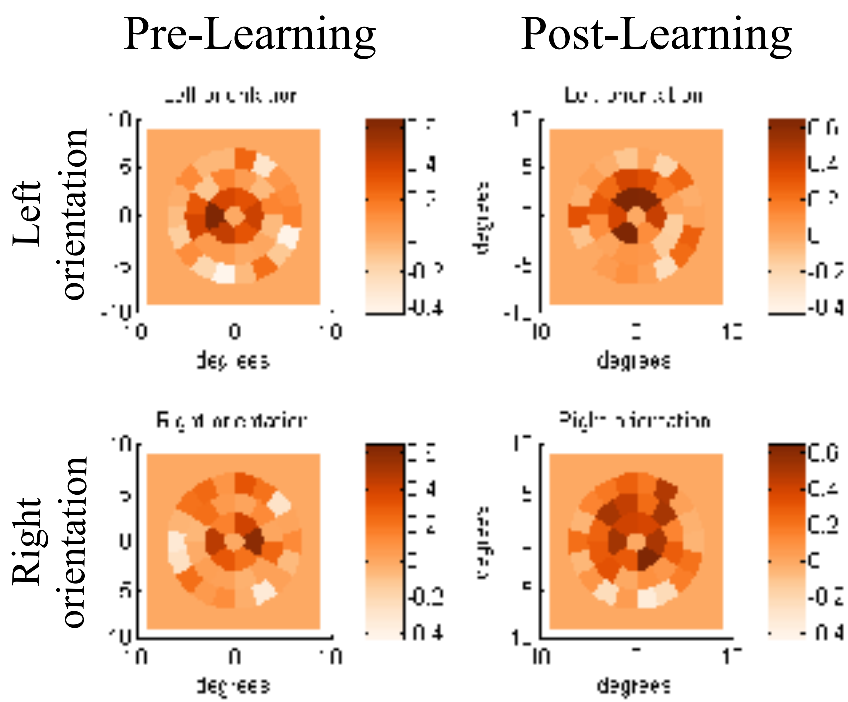
Figure; Behavioural decision templates for each day of training. Raw data values.

Data Analysis - individual subjects (S01)



Figure; Behavioural decision templates for each day of training. Averaged across rings.

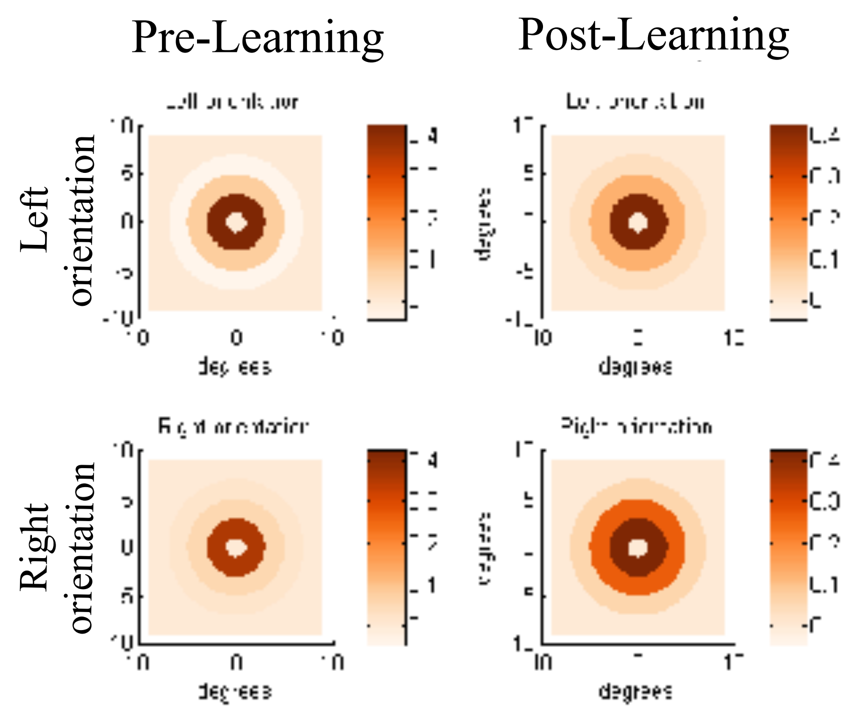
Data Analysis - individual subjects (S02)



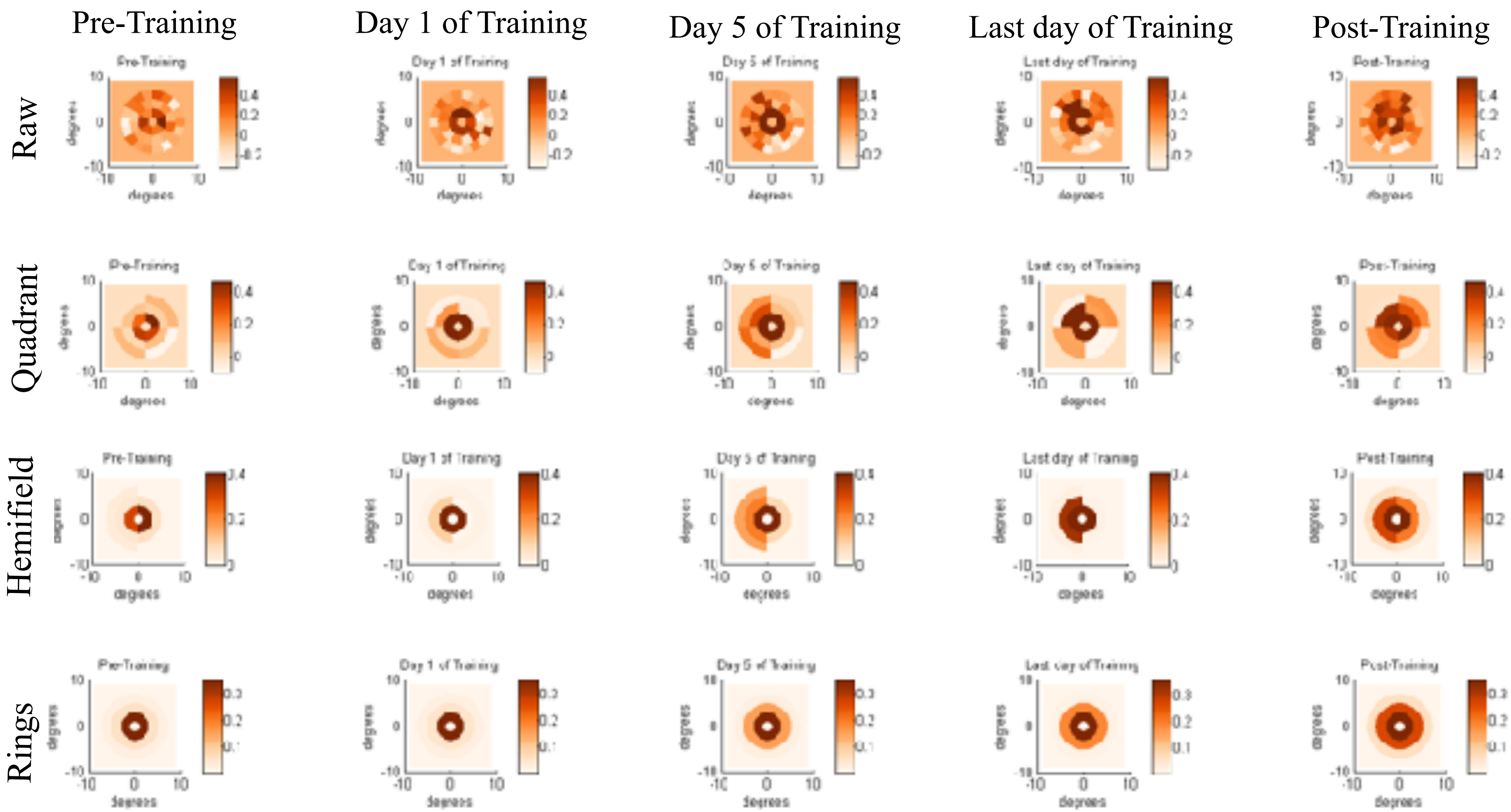
Figures. Training based improvements in decision templates. Here for both orientations. S02 trained on the right orientation.

Upper left figure. Raw data

Lower right figure. Each ring show the mean over all values associated to stimuli that belong to that same ring.

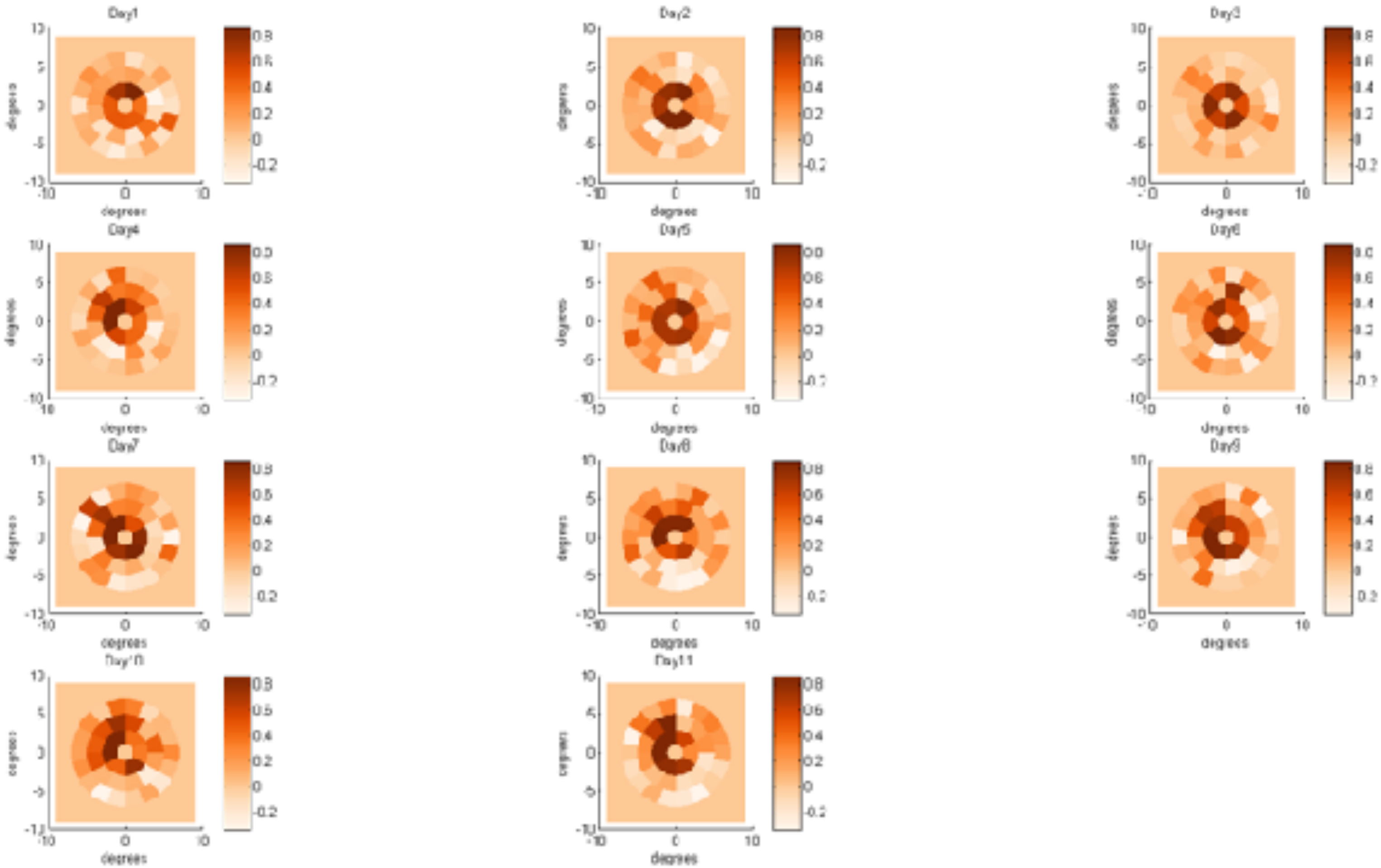


Data Analysis - individual subjects (S02)



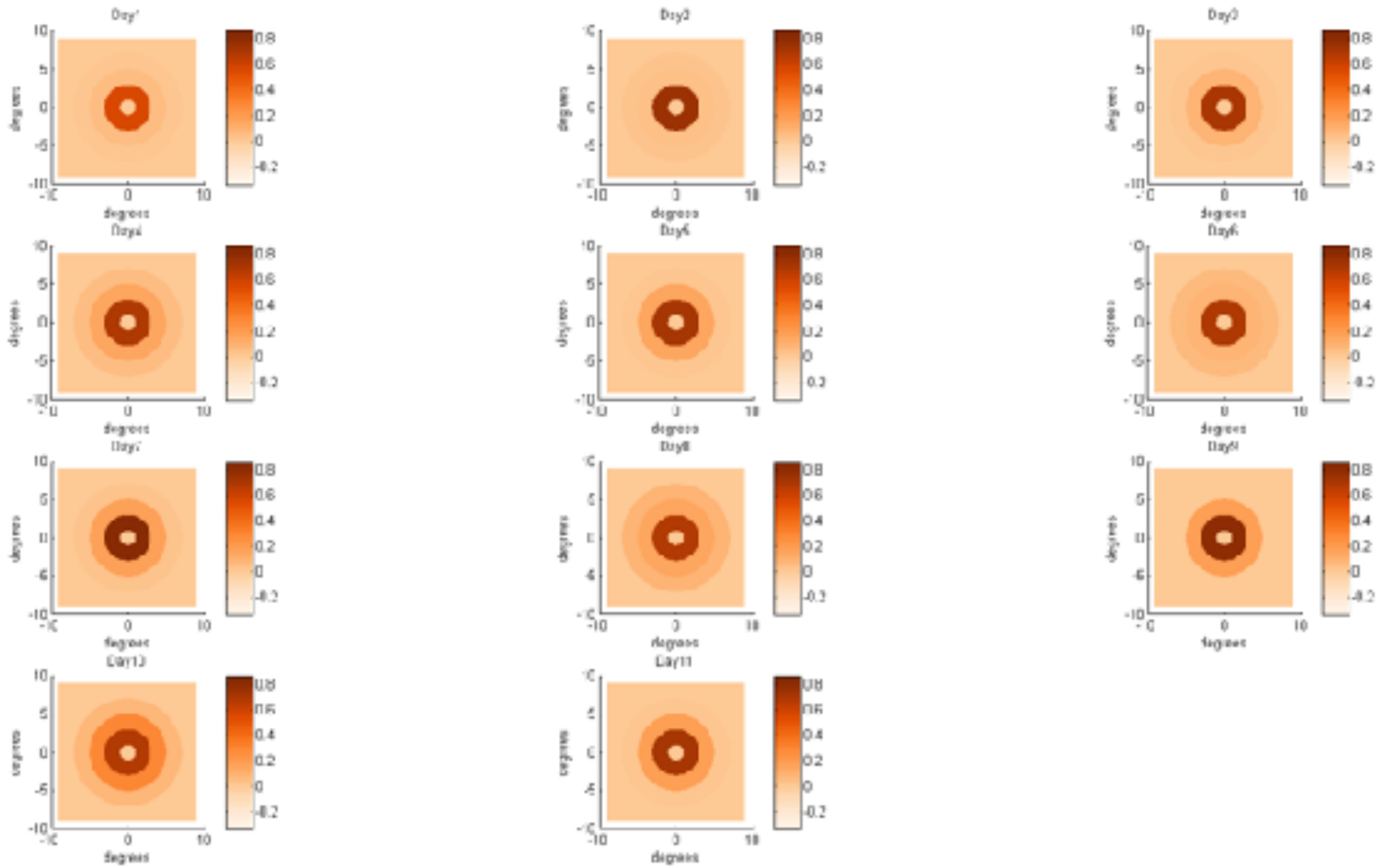
Figure; Behavioural decision templates over time. Raw data values.

Data Analysis - individual subjects (S02)



Figure; Behavioural decision templates for each day of training. Raw data values.

Data Analysis - individual subjects (S02)



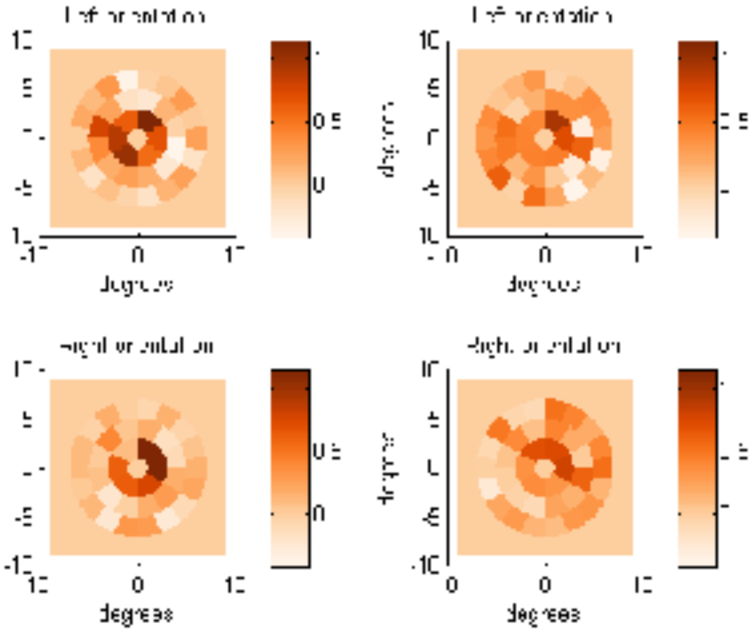
Figure; Behavioural decision templates for each day of training. Averaged across rings.

Data Analysis - individual subjects (S03)

Pre-Learning | Post-Learning

Left orientation

Right orientation



Figures. Training based improvements in decision templates. Here for both orientations. S03 trained on the left orientation.

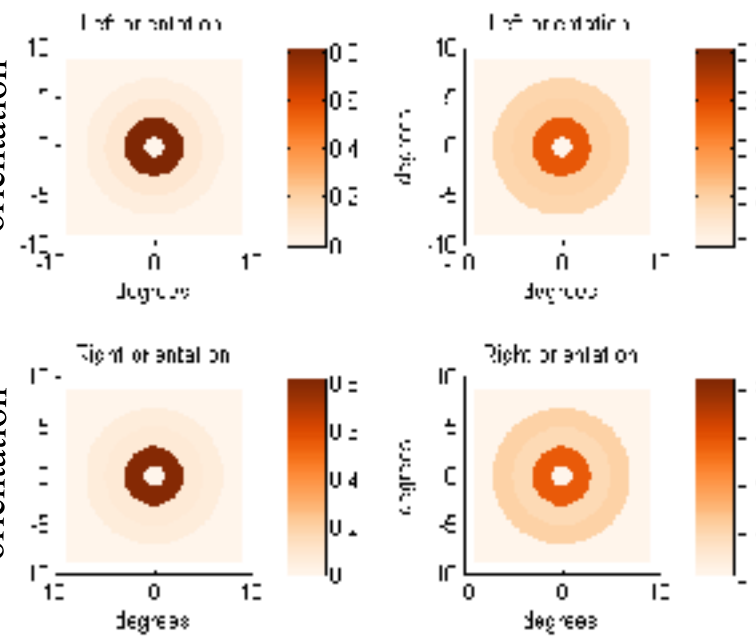
Upper left figure. Raw data

Lower right figure. Each ring show the mean over all values associated to stimuli that belong to that same ring.

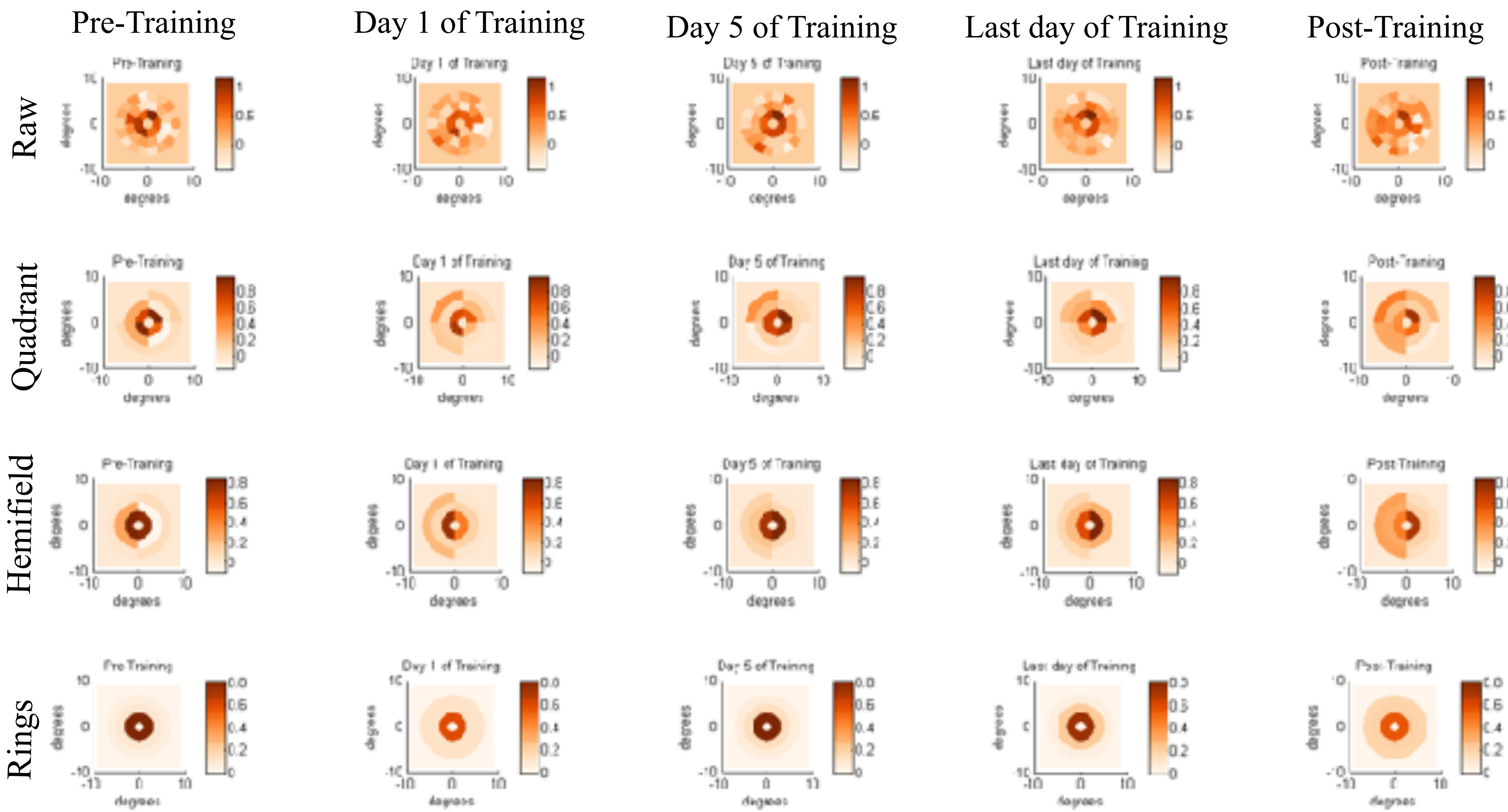
Pre-Learning | Post-Learning

Left orientation

Right orientation

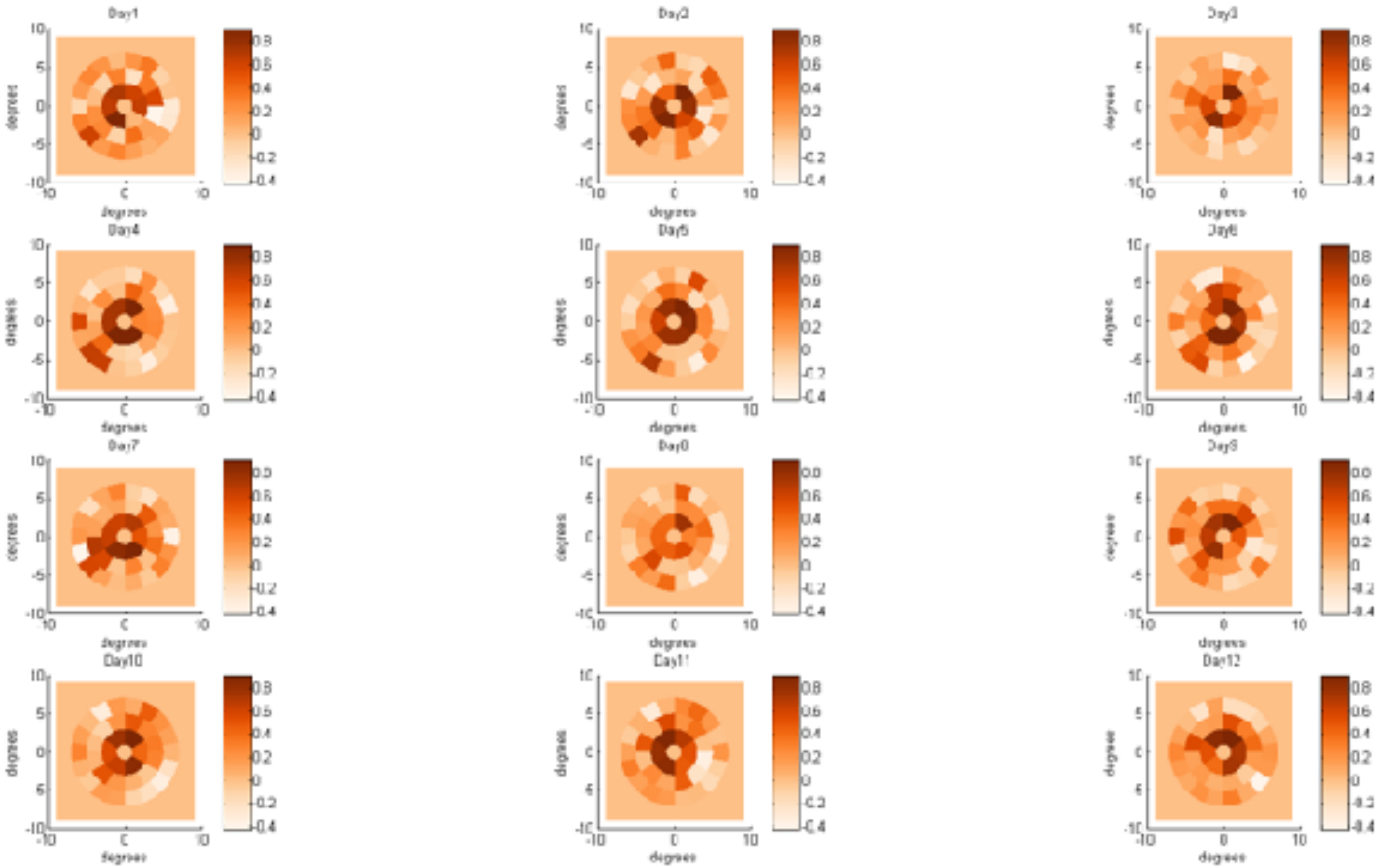


Data Analysis - individual subjects (S03)



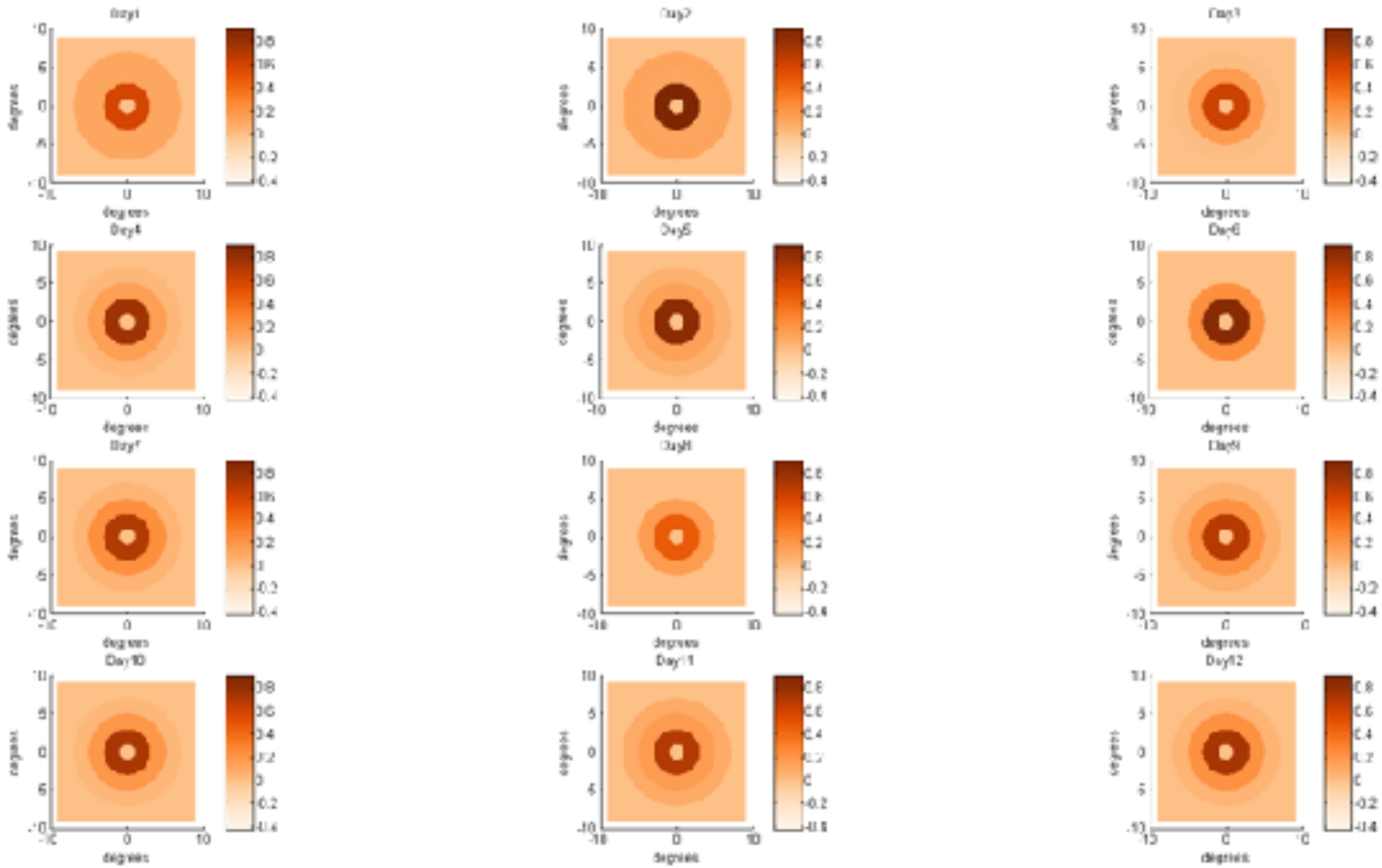
Figure; Behavioural decision templates over time. Raw data values.

Data Analysis - individual subjects (S03)



Figure; Behavioural decision templates for each day of training. Raw data values.

Data Analysis - individual subjects (S03)

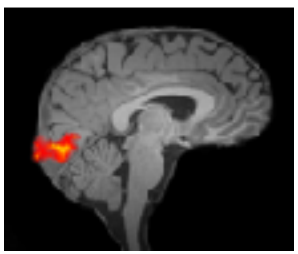


Figure; Behavioural decision templates for each day of training. Averaged across rings.

Data Analysis - fMRI

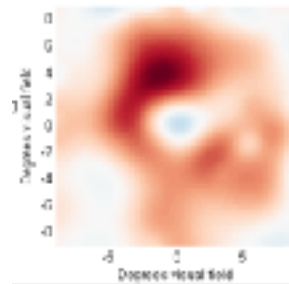
- fMRI & fMRI modeling techniques:
  - Analyse overall BOLD response in a whole brain analysis and compare between attention and training conditions
  - Standard population receptive field mapping procedures (Dumoulin & Wandell, NeuroImage, 2008)
  - Reconstruct the internal representation of the stimulus in retinotopic areas, and compare between attention and training conditions

Brain activity



Multivariate analyses

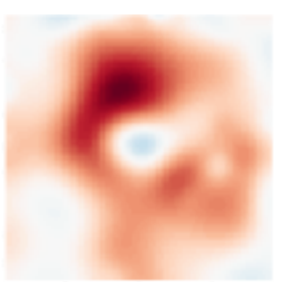
Reconstructed stimulus



Grosenick et al., NeuroImage, 2012, Schoenmakers et al., 2012, NeuroImage

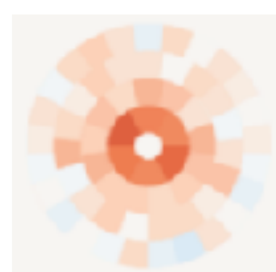
  - Correlate brain and behavioral data

Template from brain data



Predict behavior from brain data?

Template from behavioral data



Data Analysis:

Steps for analyzing the functional data:

- Preprocess
  - Motion correction
  - De-trending (not on the pRF runs, as mrVista does de-trending while running the pRF model)

- Population receptive field model*:
  - For each run, de-mean all voxels, using as baseline the mean activity across time
  - Average time-series across all pRF runs
  - Run mrVista's pRF code (hacking it by commenting out MrVista's normalization procedures)
  - Recover the amplitude of the receptive fields by predicting the time-series given 1) the receptive field size and location 2) the stimulus position over time.
  - Manually draw boarders of V1, V2 and V3

- Functional data of the main experiment:
  - Run GLM on raw time-series in order to get one intercept per run.
  - Use this intercept to normalize our time-series (we have only 12 sec of fixation per block, that might not be enough for the BOLD signal to return to baseline)
  - *Data cleaning*: Use only voxels for which the pRF model explain at least 10% of the variance and that have a receptive field with sigma > 0.49 degrees.
  - Shift time-series of 3TR when computing the average activation over time per condition.

* The transformation from the Native space to the T1, that is needed to manually draw retinotopic regions, it is done using nearest neighbors normalization. So, we can convert back to the Native space pRF estimates, as nearest neighbors make copies of time-series without interpolating.

GraphRidge: details and ground truth

Data Analysis:

GraphRidge regression: reconstruct stimuli from human brain activity (fMRI)

Goal: Reconstruct the presented stimulus from brain activity in order to test the effects of learning and attention on the sensory representation. We will also test whether the change in the sensory representation is linked to the training-based change in behavior (as observed through the behavioral decision templates).

Why?What are the benefits?

- It weighs the contribution of each voxel by taking into account their receptive field properties (as estimated by pRF mapping) as well as its activity profile in the condition of interest
- This will enable us to *correlate brain activity with behavioral decision templates* across visual space. Indeed, the reconstructed stimulus is expressed in pixel values, so we can draw borders and split between rings.

Open questions:

- How much smoothing adds/creates the model? What is our precision in visual space? Shall we use same value of lambda?
- Is this the best model that we can use? Should we try also graph-net, elastic-net etc.?

Data Analysis:

GraphRidge regression: reconstruct stimuli from human brain activity (fMRI)

What is it? How does it works?:

- Formula $$B = argmin(y - XB) + L * P(B)$$
- It uses L2 norm $$\lambda_2 = P(B) = \sum_{j=1}^{m} B_j^2$$
- It uses a graphical dependency matrix G (which simply says for each pixels how many and which pixels are surrounding it. Closer pixels should have closer values),that induces smoothness
- Solution to the regression:

$$\beta = (X'X + \lambda(1 - \alpha) * G)/X'Y)$$

Variables:

- X = regression model, which are pRFs expressed in pixels' values. *(nrOfVox * nrOfPixels)*
- Y = voxels' activation. (mean BOLD, *nrOfVox * 1*)
- lambda & alpha = hyperparameters. They define the type and the amount of normalisation. Here, alpha is set at 0 which means that we are using L2 norm.
- G = graphical dependency matrix

Data Analysis:

GraphRidge regression: reconstruct stimuli from human brain activity (fMRI)

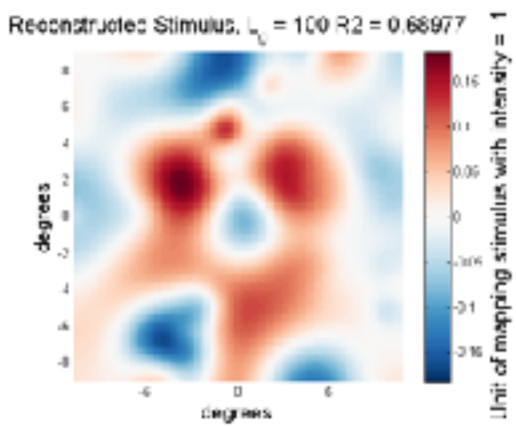
Ground truth:

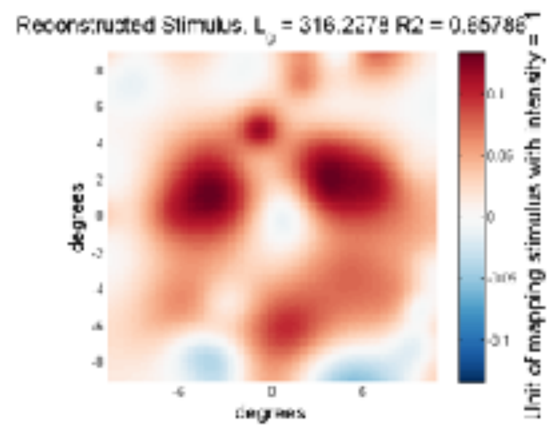
Stim 3.5 degree radius

18 degrees

Stim 5.5 degree radius

18 degrees

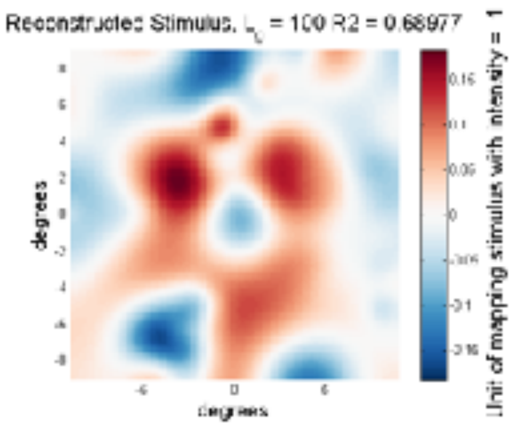




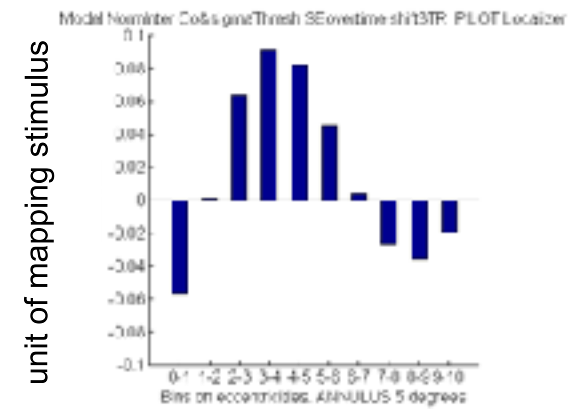
Data Analysis:

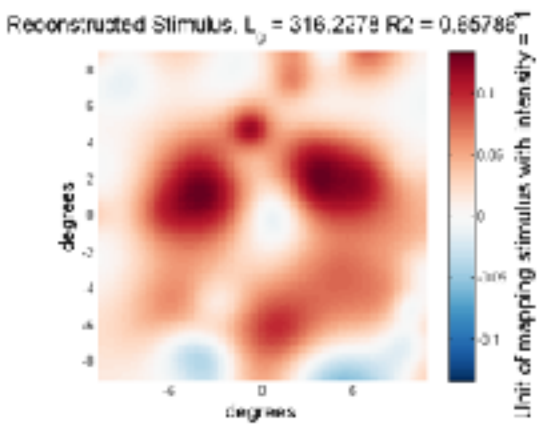
GraphRidge regression: reconstruct stimuli from human brain activity (fMRI)

Ground truth:

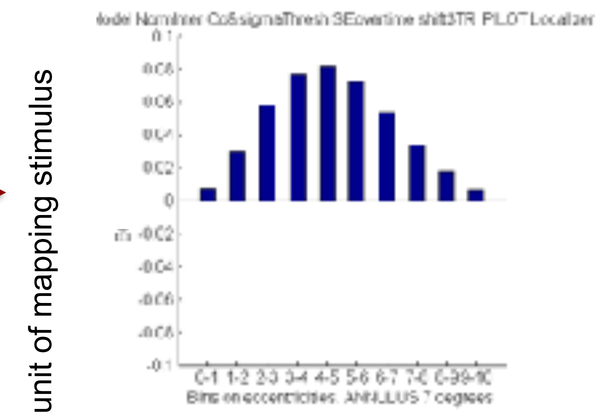


Mean over pixels that fall within certain eccentricities





Mean over pixels that fall within certain eccentricities



S02

Pre-Training

Data plotted on the inflated brain
(T1 space)

Data Analysis:

Figure 1. Eccentricity maps

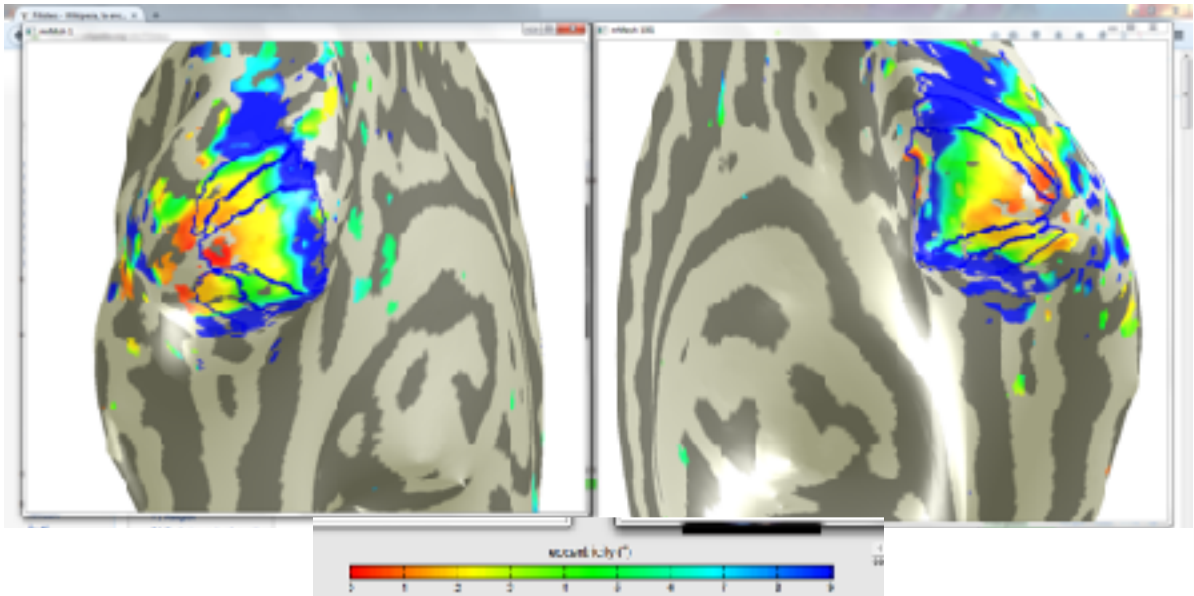
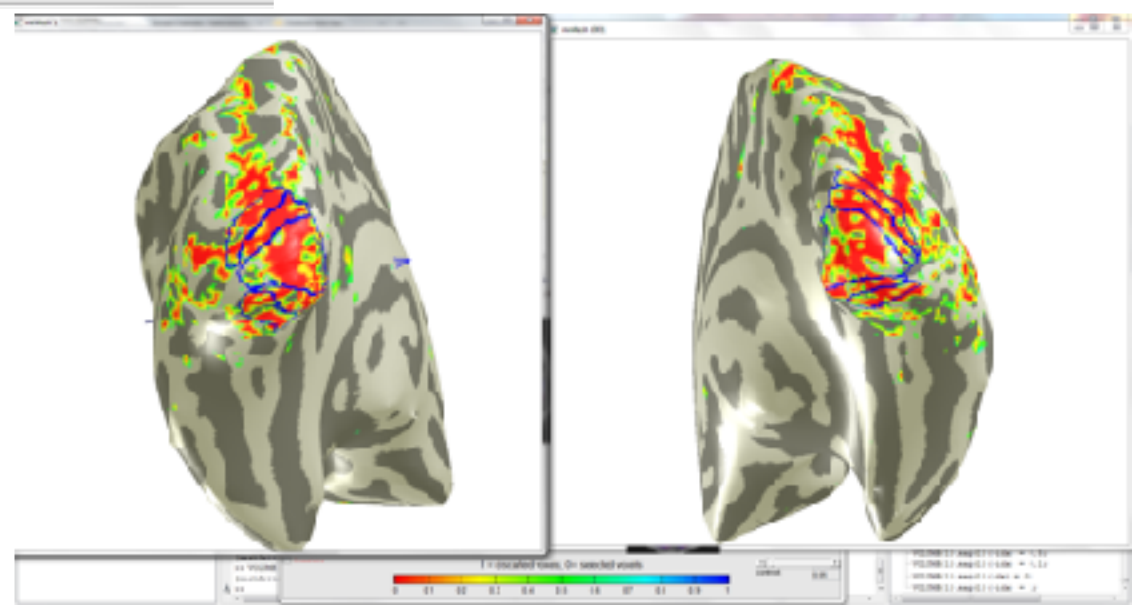


Figure 2. The map shows voxels' selection used for the Graphridge model. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance (voxels without color but within the drawn ROIs) and 2) pRF is at least 0.5 degrees VA in diameter (green voxels).



Data Analysis:

Figure 1. T-values from a GLM with contrast STIM_ON

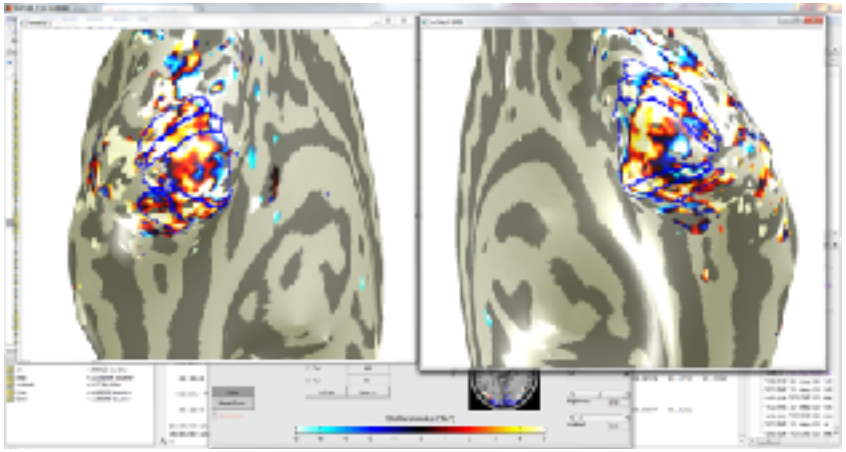


Figure 2. T-values from a GLM with contrast for the attended condition

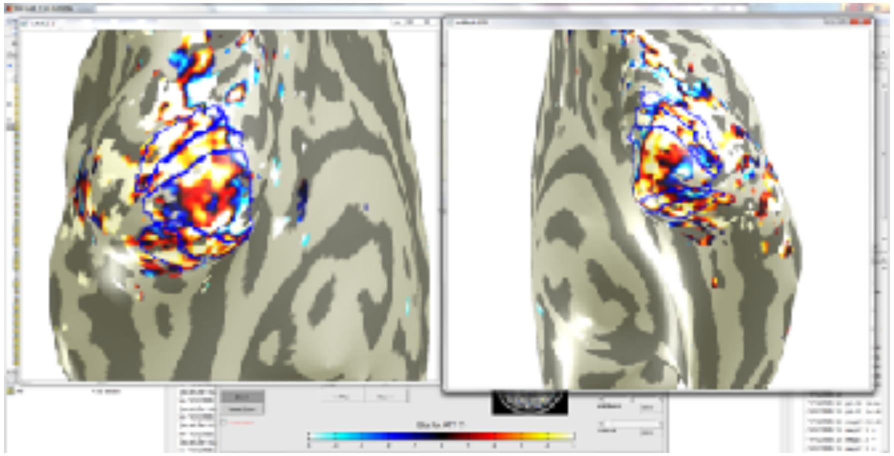


Figure 3. T-values from a GLM with contrast for the unattended condition

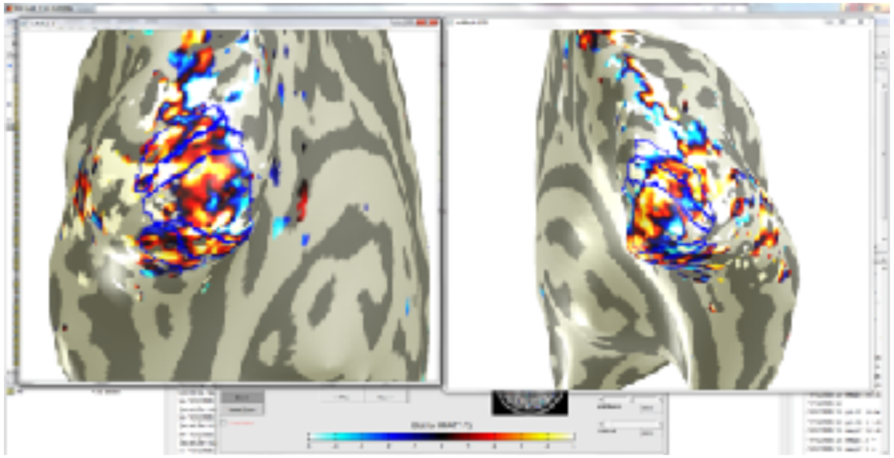
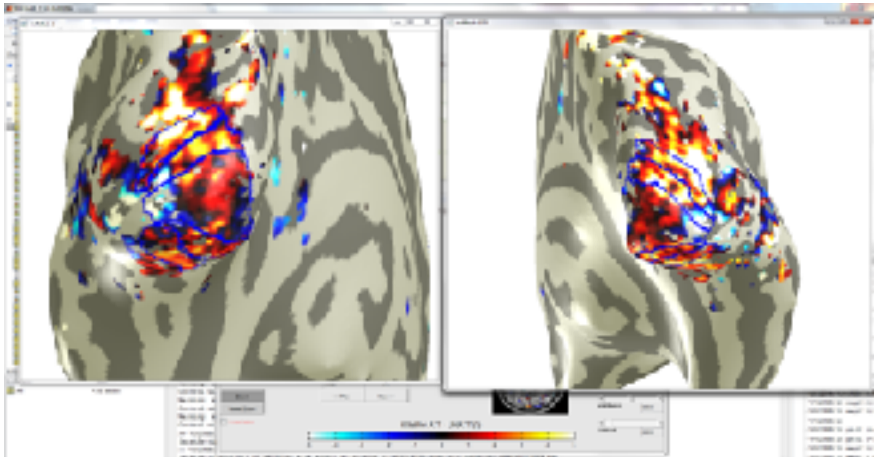


Figure 4. T-values from a GLM with contrast attended minus unattended



Data Analysis:

Pre-Training, S02

Voxels selected based on pRF analysis

Figure 1

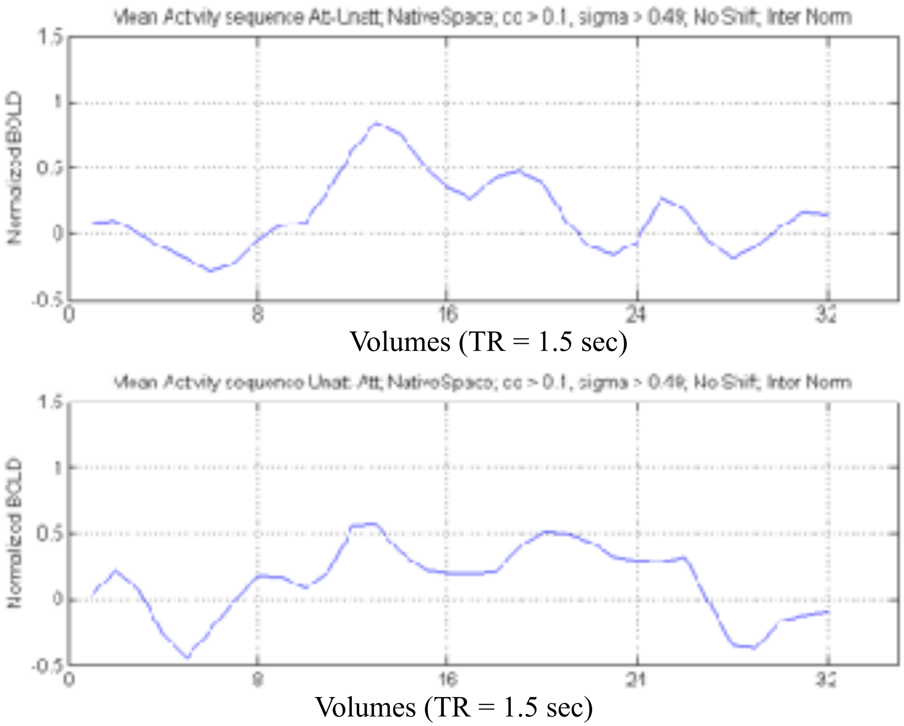


Figure 1. Mean BOLD. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter. The top row shows the sequence of blocks F-A-U-F while the bottom row shows the sequence F-U-A-F.

Figure 2

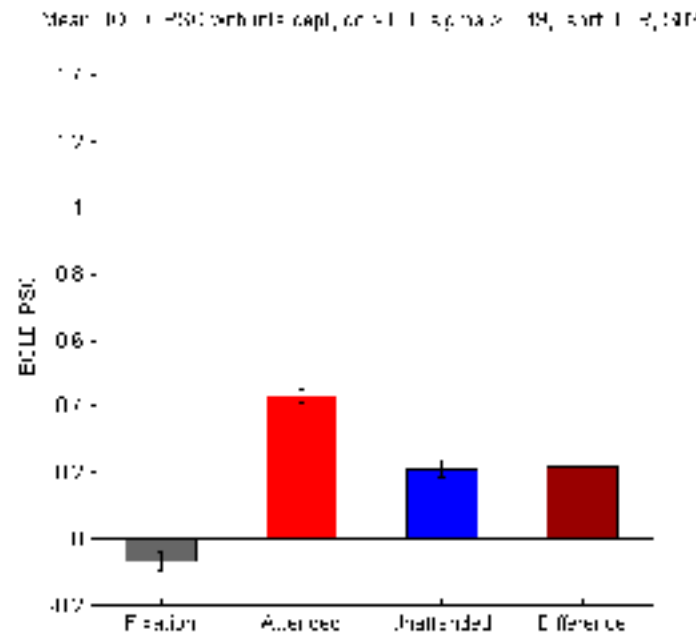


Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Pre-Training, S02

Voxels selected based on GLM/ stimulus-driven activity

Figure 1

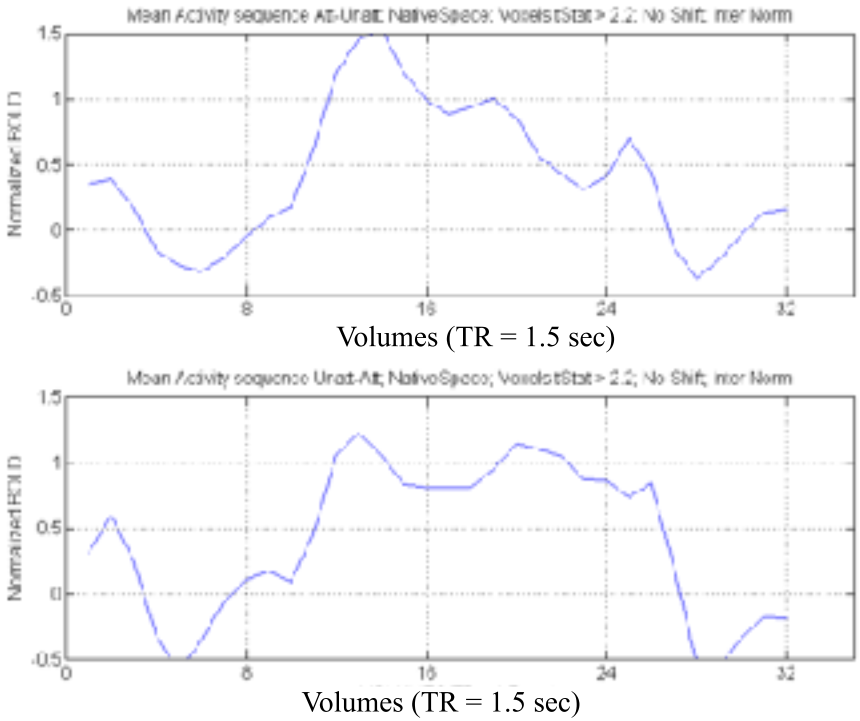


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Figure 2

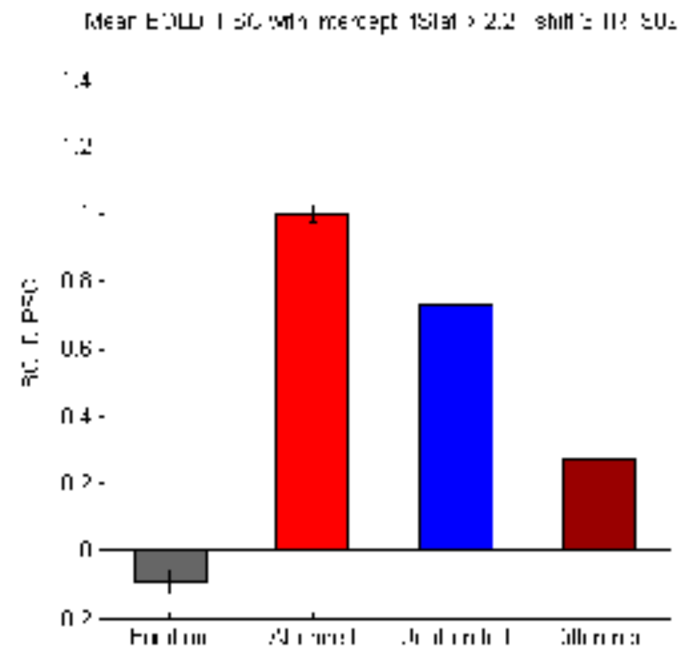
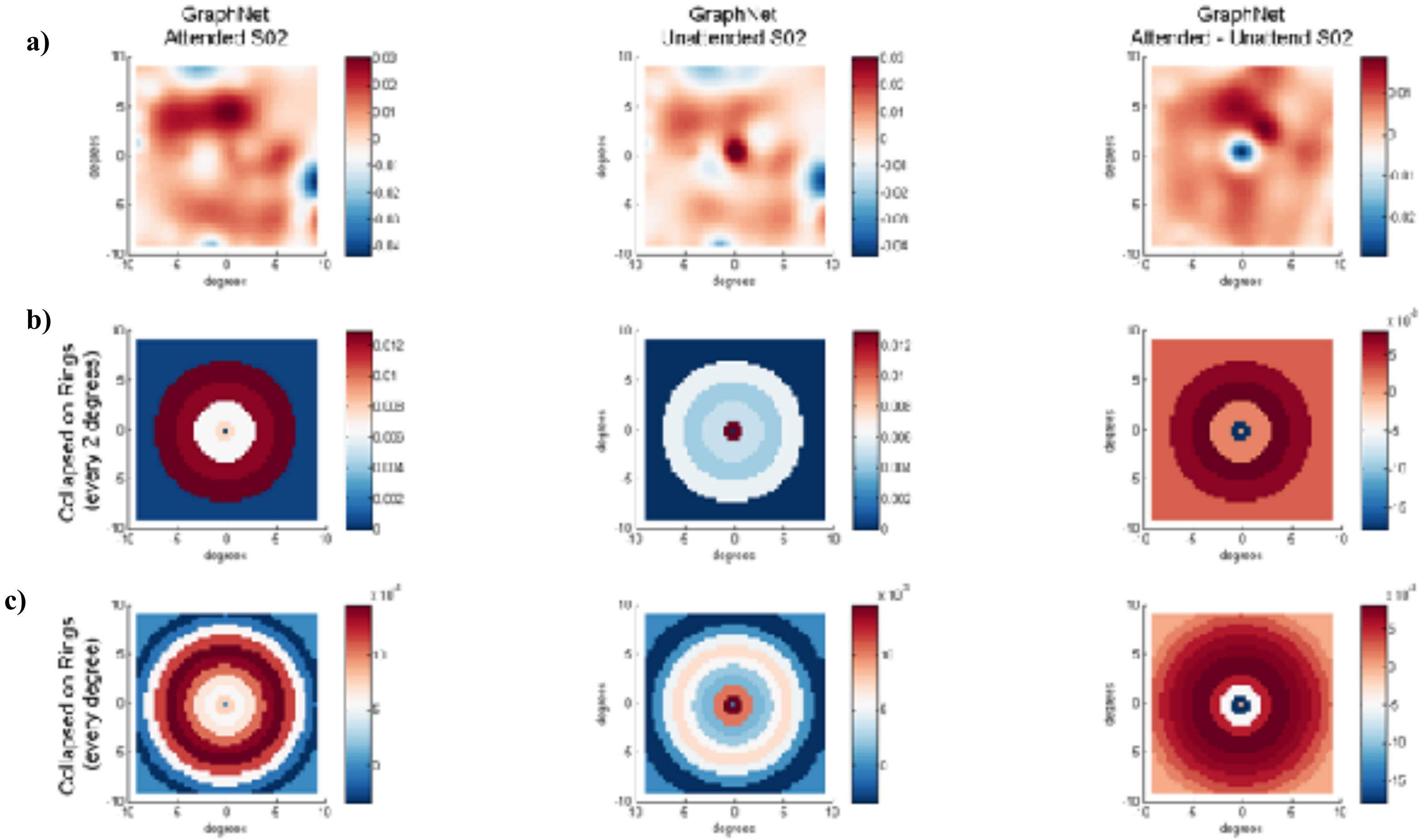


Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Pre-Training S02

Grid used here is 50 x 50 pixels



a) GraphRidge model. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter **b)** Average across pixel values. Ring size matches the size of the presented stimulus **c)** Average across pixel values. Ring depicts eccentricity values.

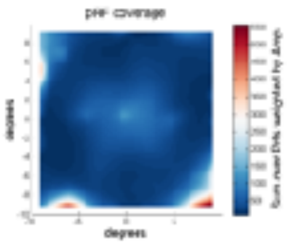
Data Analysis:

Pre-Training S02

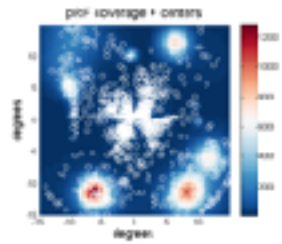
Grid used here is 50 x 50 pixels

Figure 1

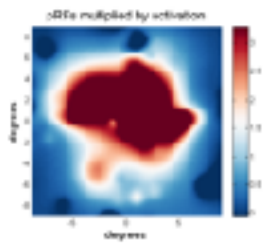
a)



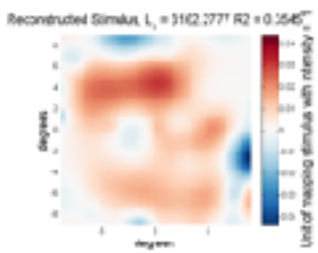
b)



c)



d)



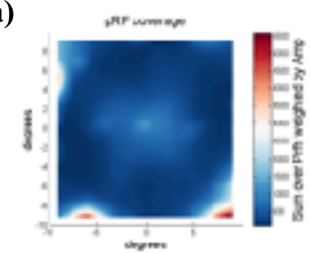
Figures: a) Sum over Gaussian receptive fields. The visual field extends up to 9 degrees. **b)** Sum over gaussian receptive fields. The visual field extends up to 15 degrees. **c)** Sum over Gaussians receptive fields multiplied by their activation during the main task. **d)** GraphRidge model.

Figure 1: Reconstructed stimulus during the **attended** condition.

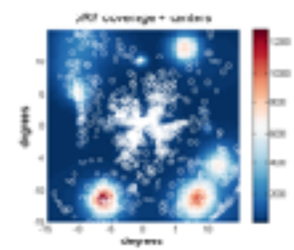
Figure 2: Reconstructed stimulus during the **unattended** condition.

Figure 2

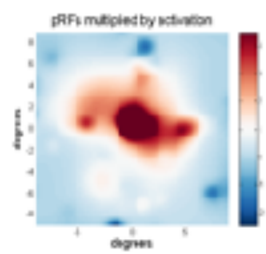
a)



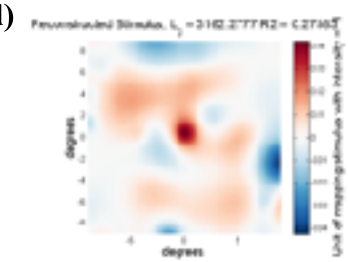
b)



c)



d)



Data Analysis:

S03, Pre-Training, all V1 to V3

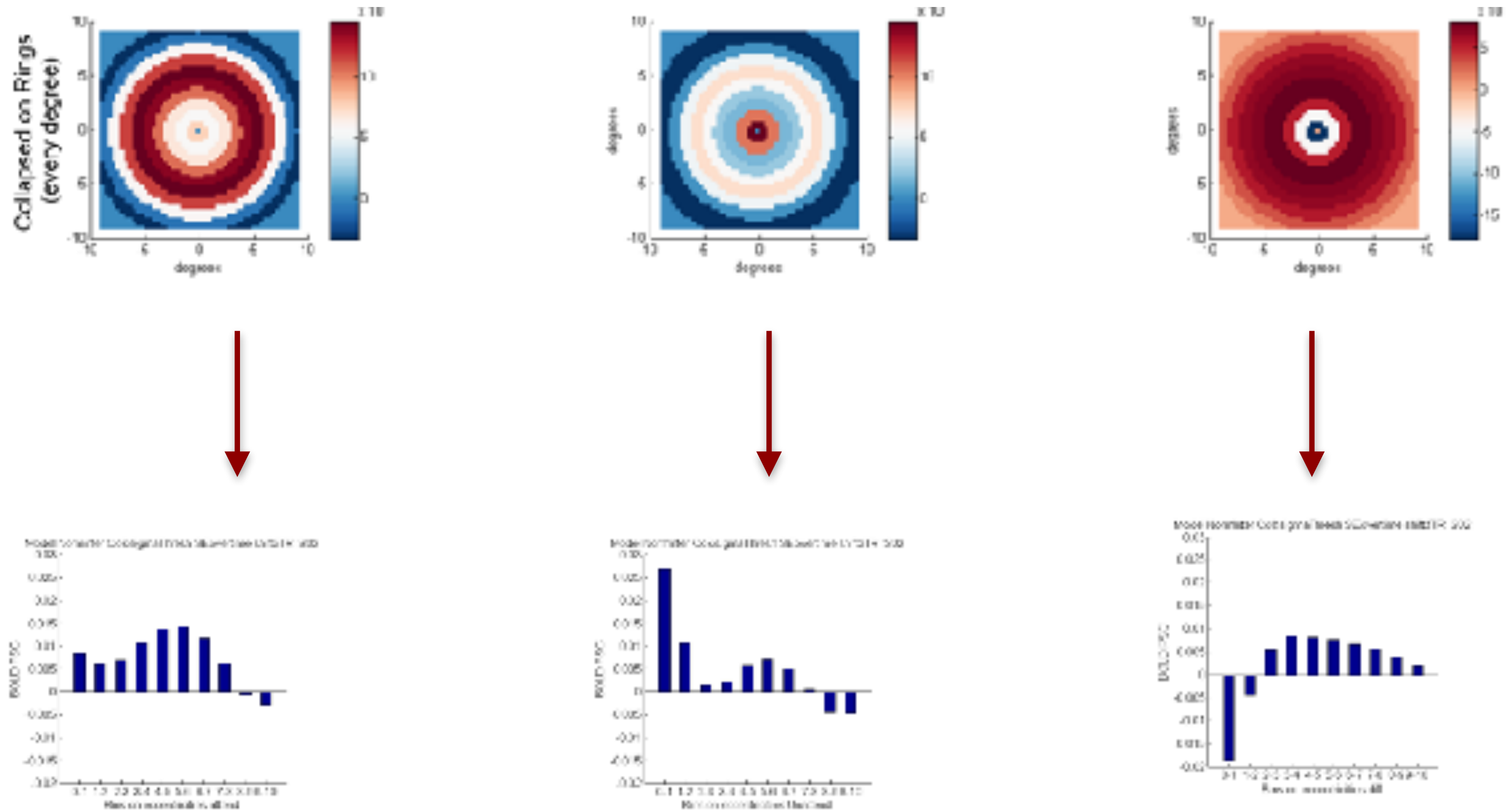
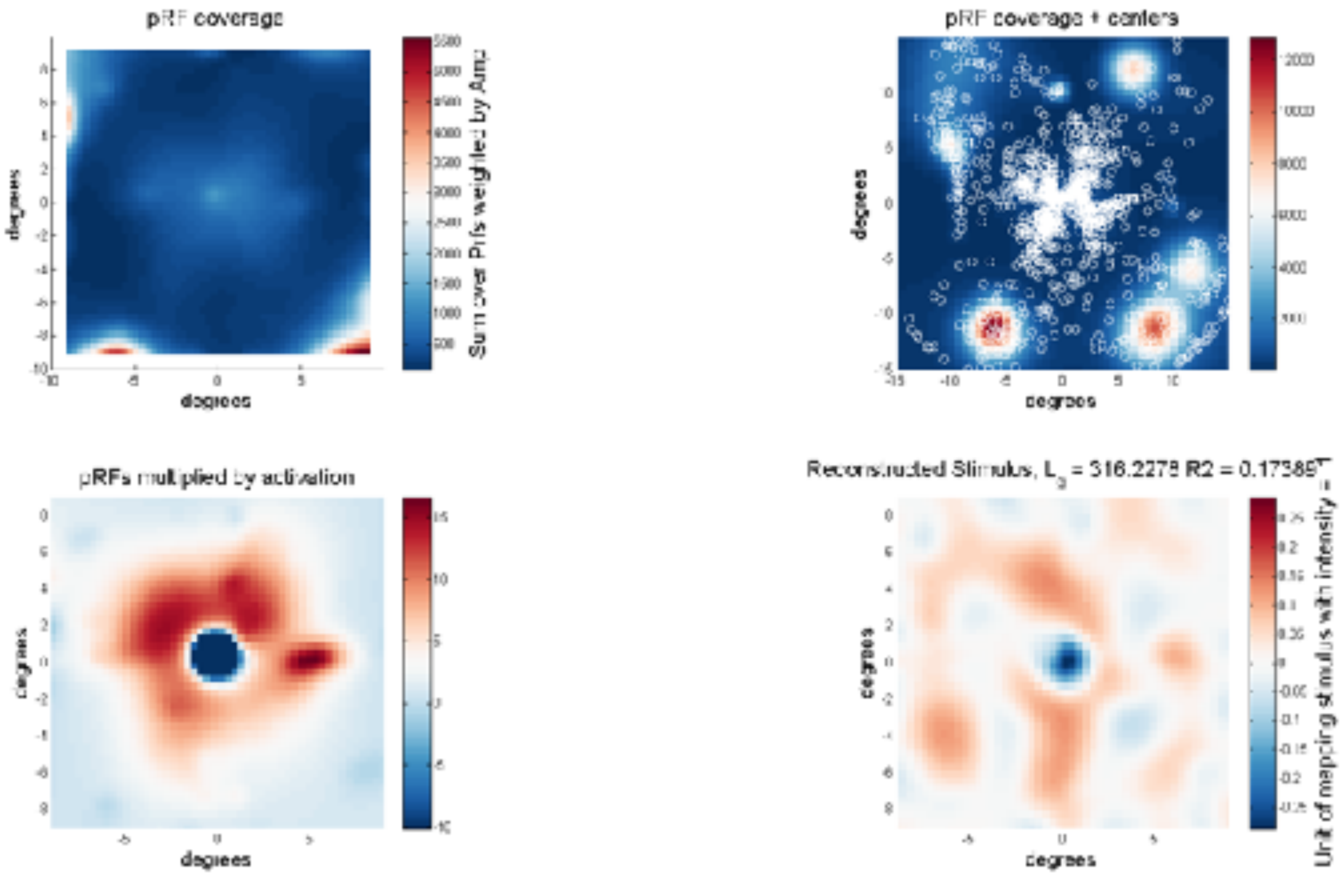


Figure:
Top plots: Average across pixel values. One ring every eccentricity.
Bottom plots: Same values but plotted in a bar plot.

Data Analysis:

S02, Pre-Training, all V1 to V3

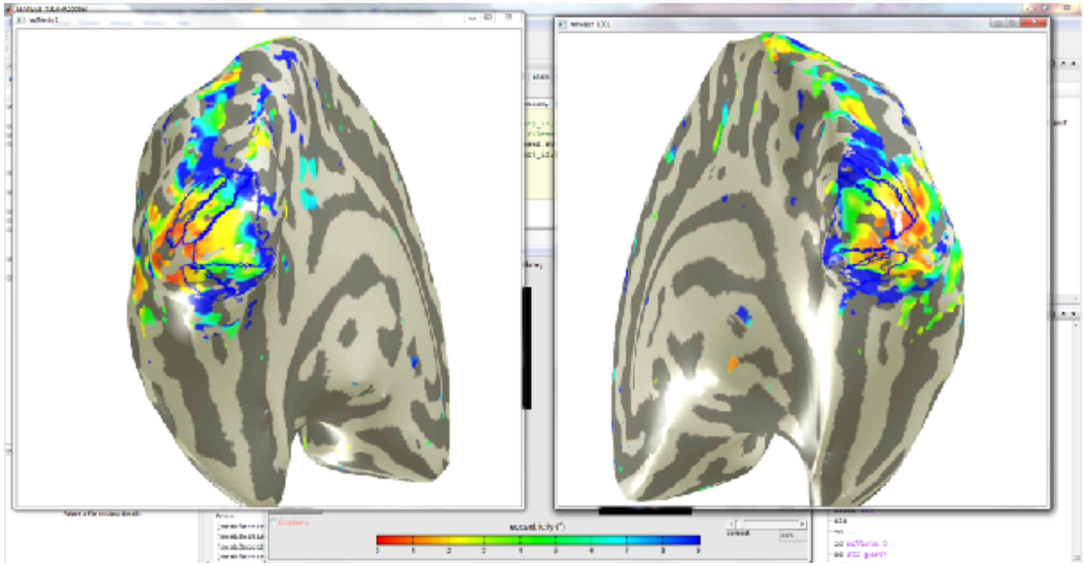


Post-Training

Data plotted on the inflated brain
(T1 space)

Data Analysis:

Figure 1. Eccentricity maps



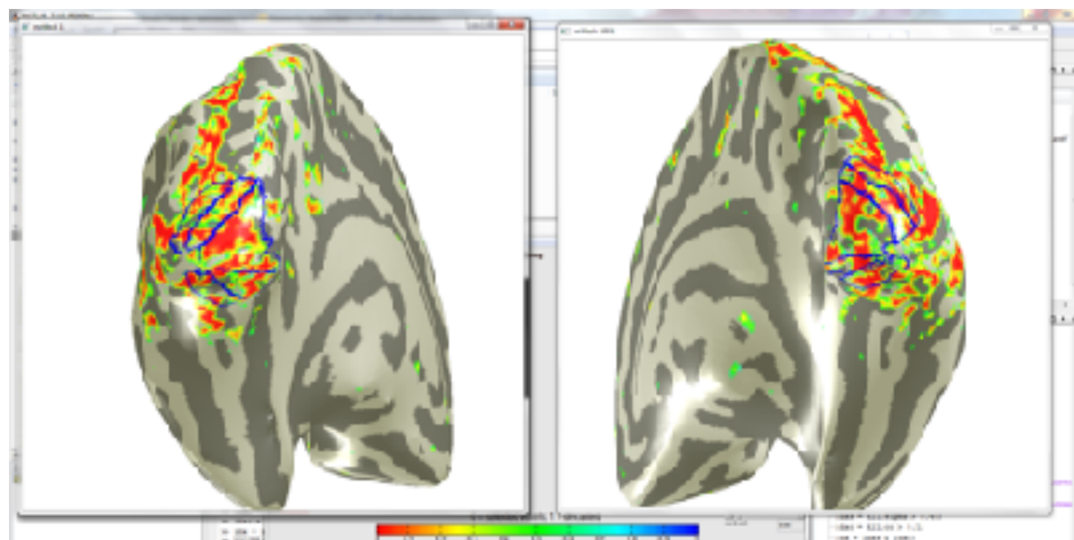


Figure 2. The map shows voxels' selection used for the Graphridge model. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance (voxels without color but within the drawn ROIs) and 2) pRF is at least 0.5 degrees VA in diameter (green voxels).

Data Analysis:

Figure 1. T-values from a GLM with contrast STIM_ON

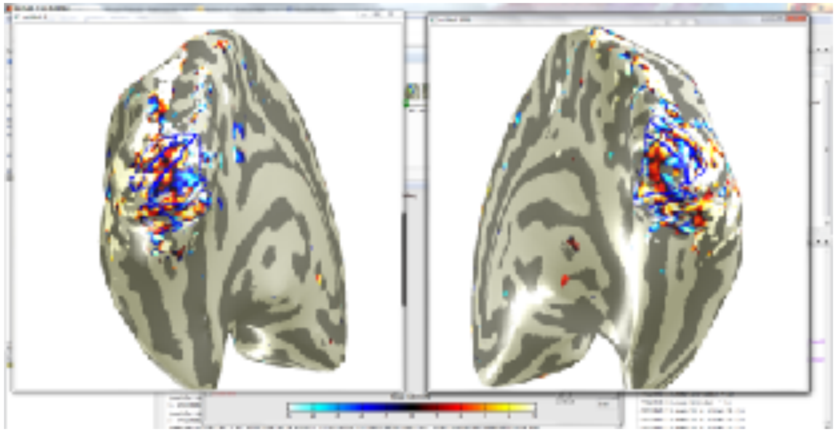


Figure 2. T-values from a GLM with contrast for the attended condition

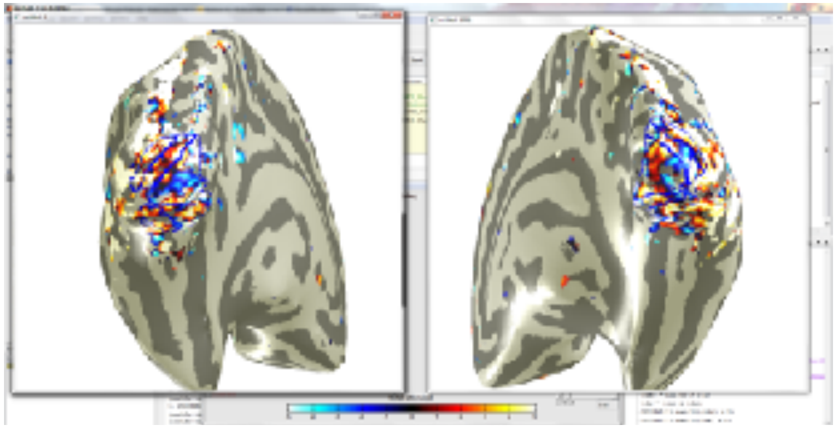


Figure 3. T-values from a GLM with contrast for the unattended condition

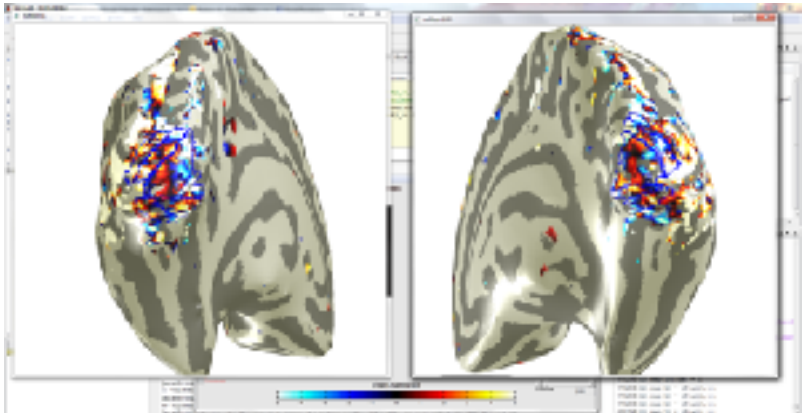
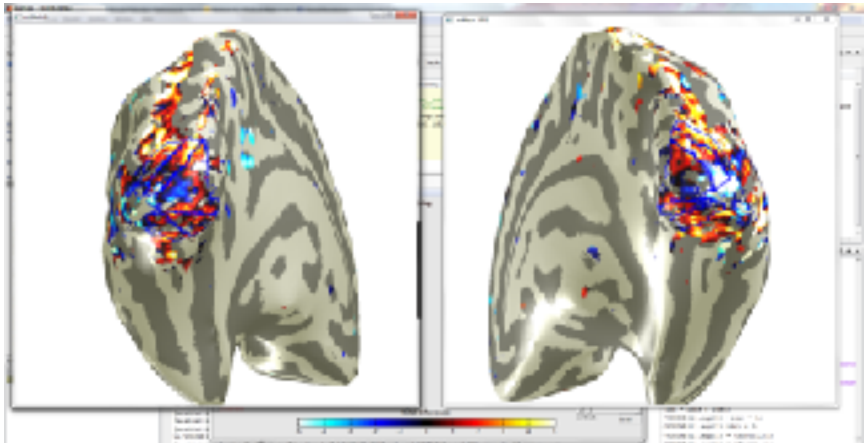


Figure 4. T-values from a GLM with contrast attended minus unattended



Data Analysis:

Pre-Training, S02
Voxels selected based on pRF analysis

Figure 1

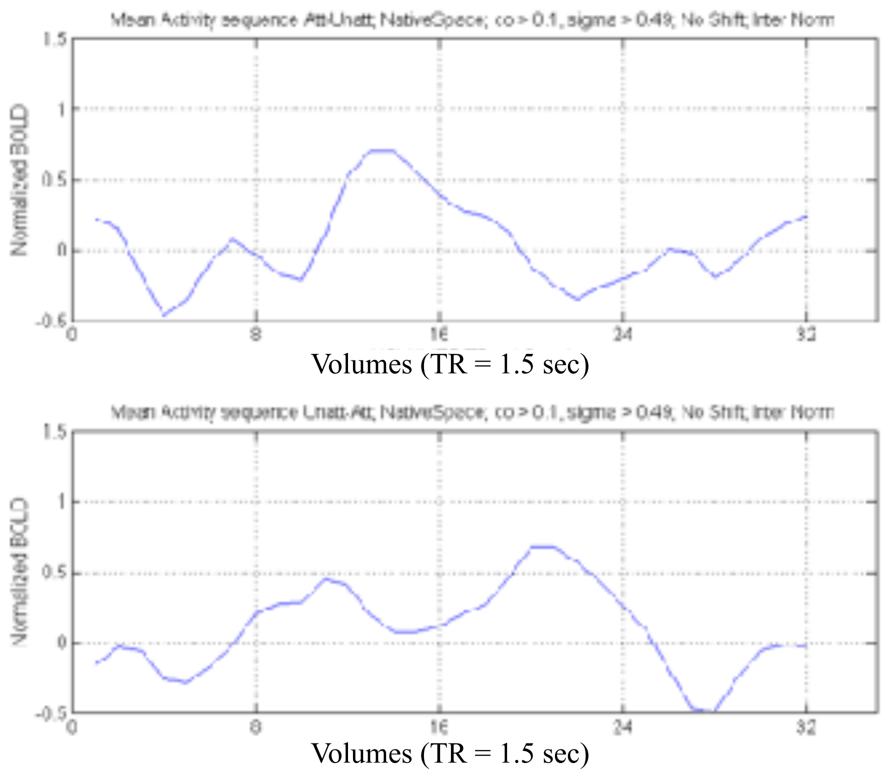


Figure 1. Mean BOLD. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter. The top row shows the sequence of blocks F-A-U-F while the bottom row shows the sequence F-U-A-F.

Figure 2

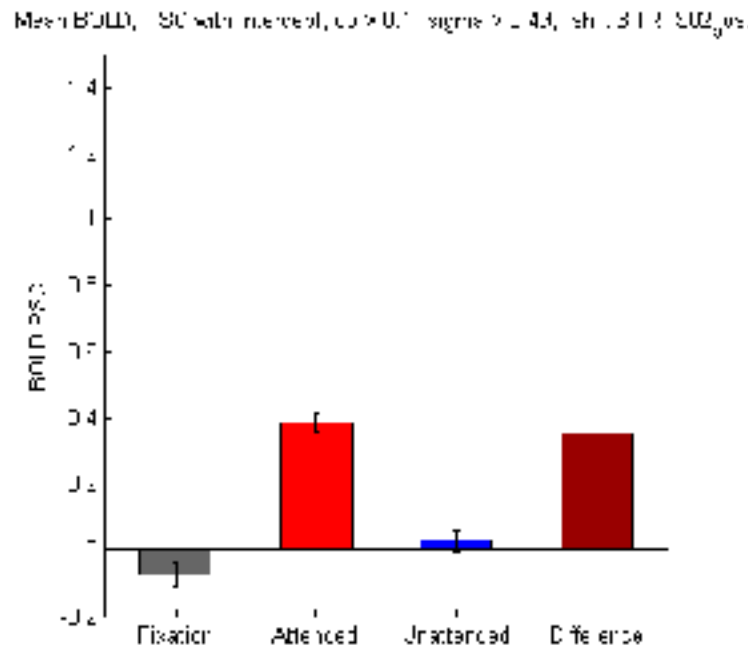


Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Pre-Training, S02

Voxels selected based on GLM/ stimulus-driven activity

Figure 1

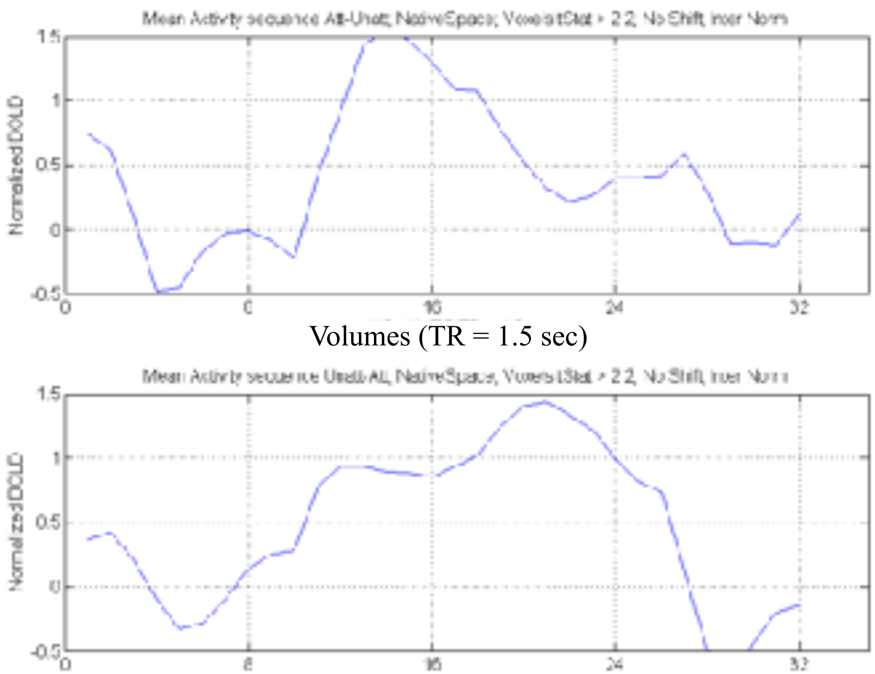


Figure 2

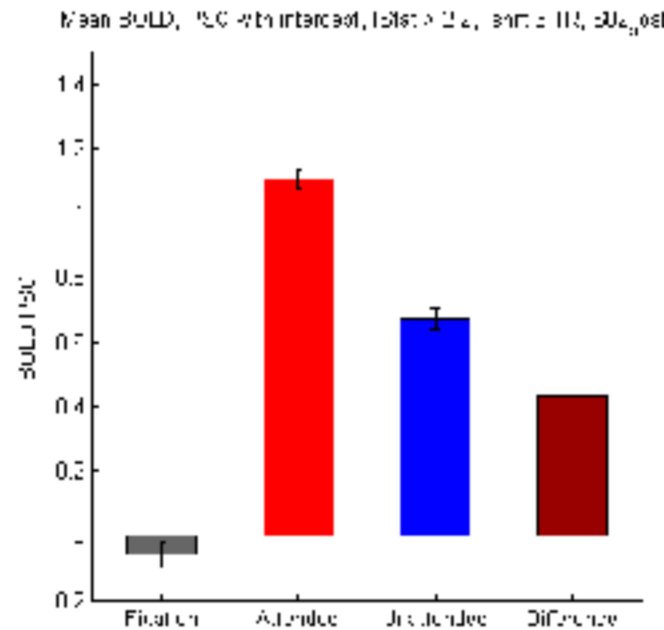


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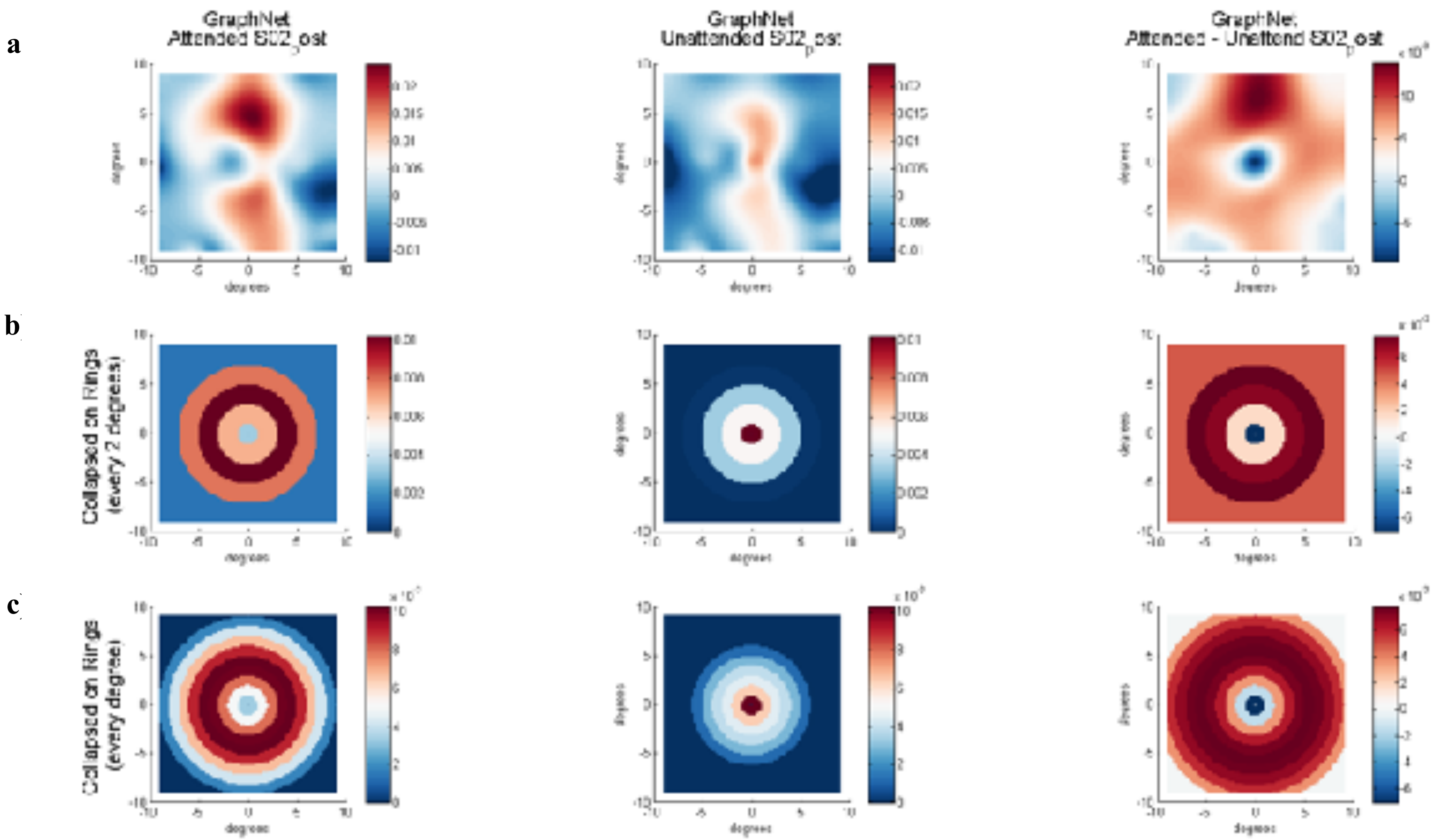
Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Post-Training S02



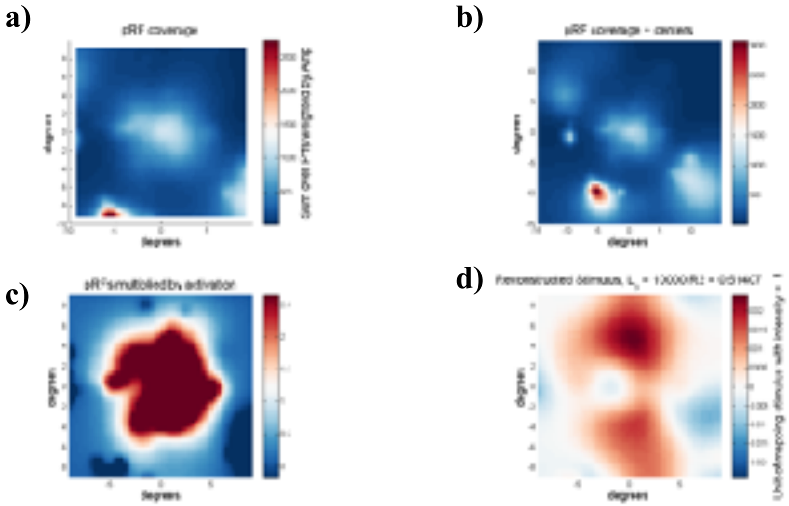
a) GraphRidge model. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter **b)** Average across pixel values. Ring size matches the size of the presented stimulus **c)** Average across pixel values. Ring depicts eccentricity values.

Data Analysis:

Post-Training S02

Grid used here is 50 x 50 pixels

Figure 1

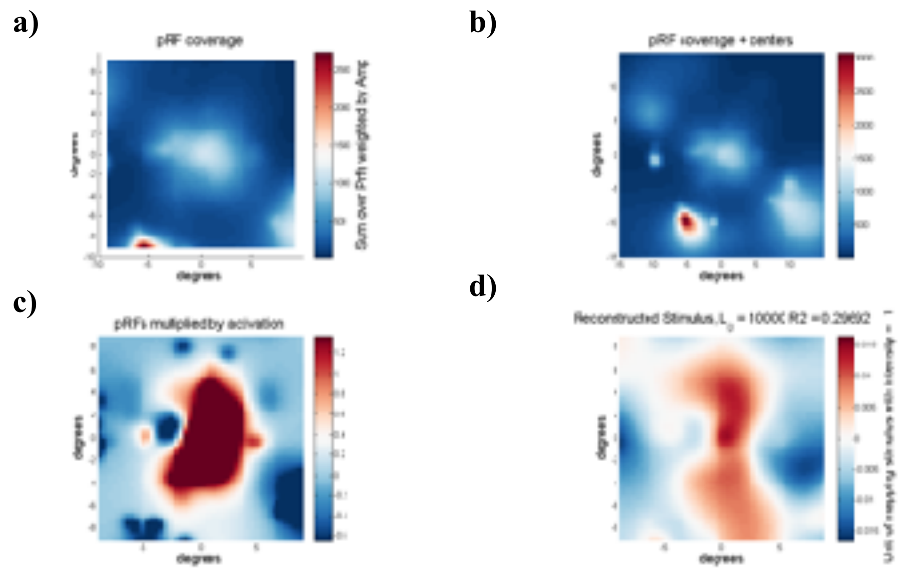


Figures: a) Sum over Gaussian receptive fields. The visual field extends up to 9 degrees. **b)** Sum over gaussian receptive fields. The visual field extends up to 15 degrees. **c)** Sum over Gaussians receptive fields multiplied by their activation during the main task. **d)** GraphRidge model.

Figure 1: Reconstructed stimulus during the **attended** condition.

Figure 2: Reconstructed stimulus during the **unattended** condition.

Figure 2

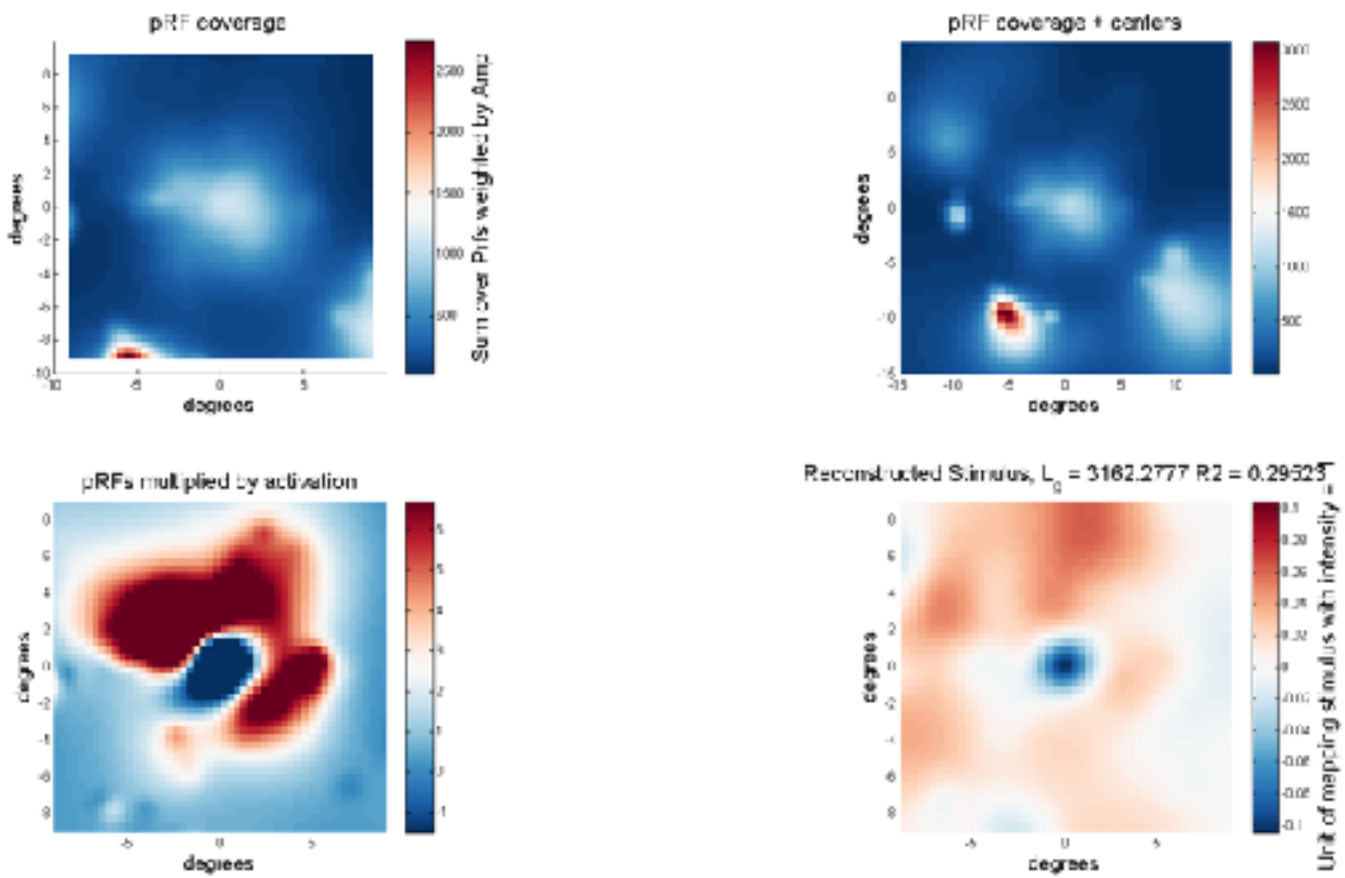


Data Analysis:

Post-Training S02

Grid used here is 50 x 50 pixels

Figure : Reconstructed stimulus using t-stats from a GLM with contrast: attended - unattended



Data Analysis:

S02, Post-Training, all V1 to V3

Figure:
Top plots: Average across pixel values. One ring every eccentricity.
Bottom plots: Same values but plotted in a bar plot.

Data Analysis:

S02, Post-Training, all V1 to V3

Learning effects

Data Analysis:

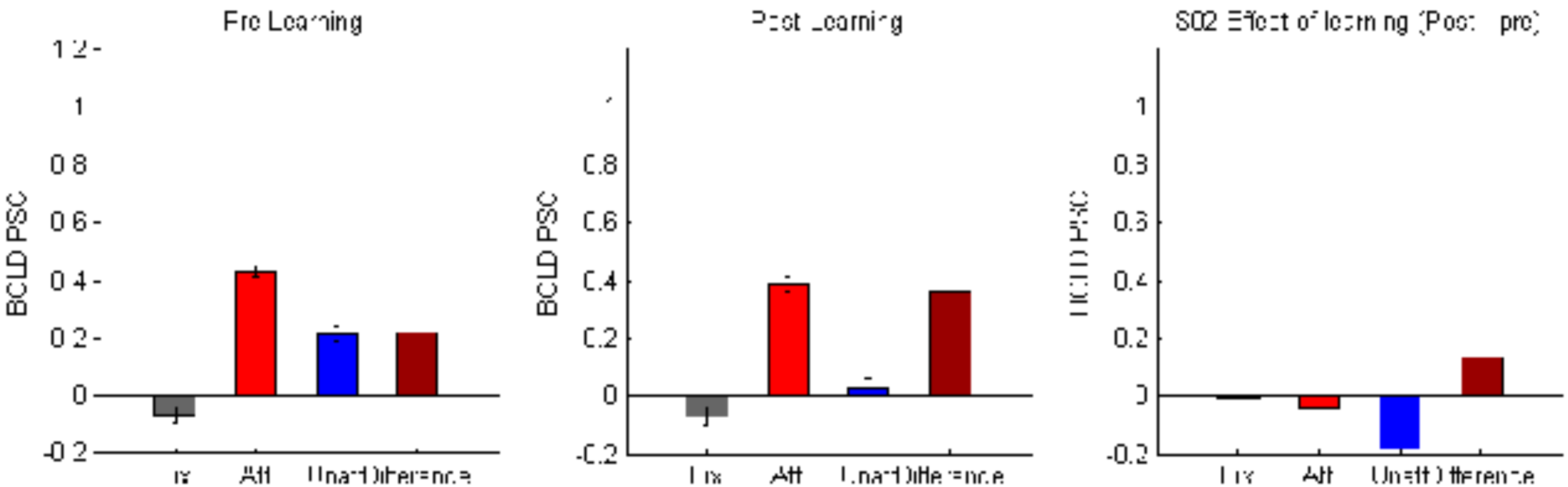


Figure. Mean BOLD of all voxels from V1, V2 and V3 for which the pRF model explained at least 10% variance and with a receptive field that extend at least for 0.5 degrees. Before averaging, the time-series had been shifted of 3TR (4.5 seconds) The normalisation of the time-series has been done using the intercept from a GLM performed over raw time-series. SEM has been computed over time on the averaged time-series across voxels.

Data Analysis:

Learning effects S02

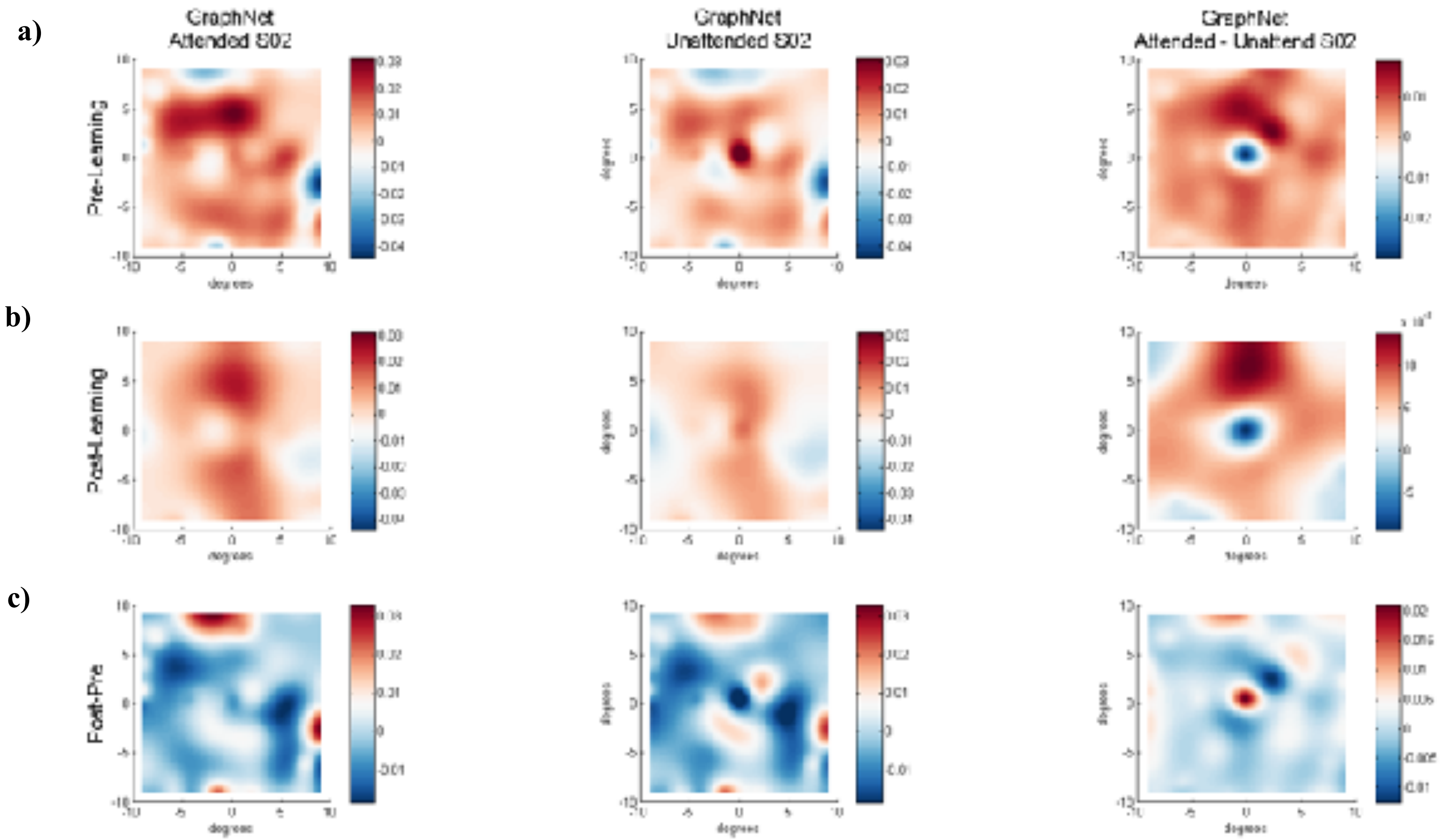


Figure. GraphRidge model: **a)** before training , **b)** after training, **c)** the plots have been created by subtracting pixel's values of post-learning reconstructed stimuli to those of the pre-learning stage. <u>However, as we did not use here the same value of lambda for all the reconstruction, the output might not be interpretable.</u>

Data Analysis:

S03, Post-Training, all V1 to V3

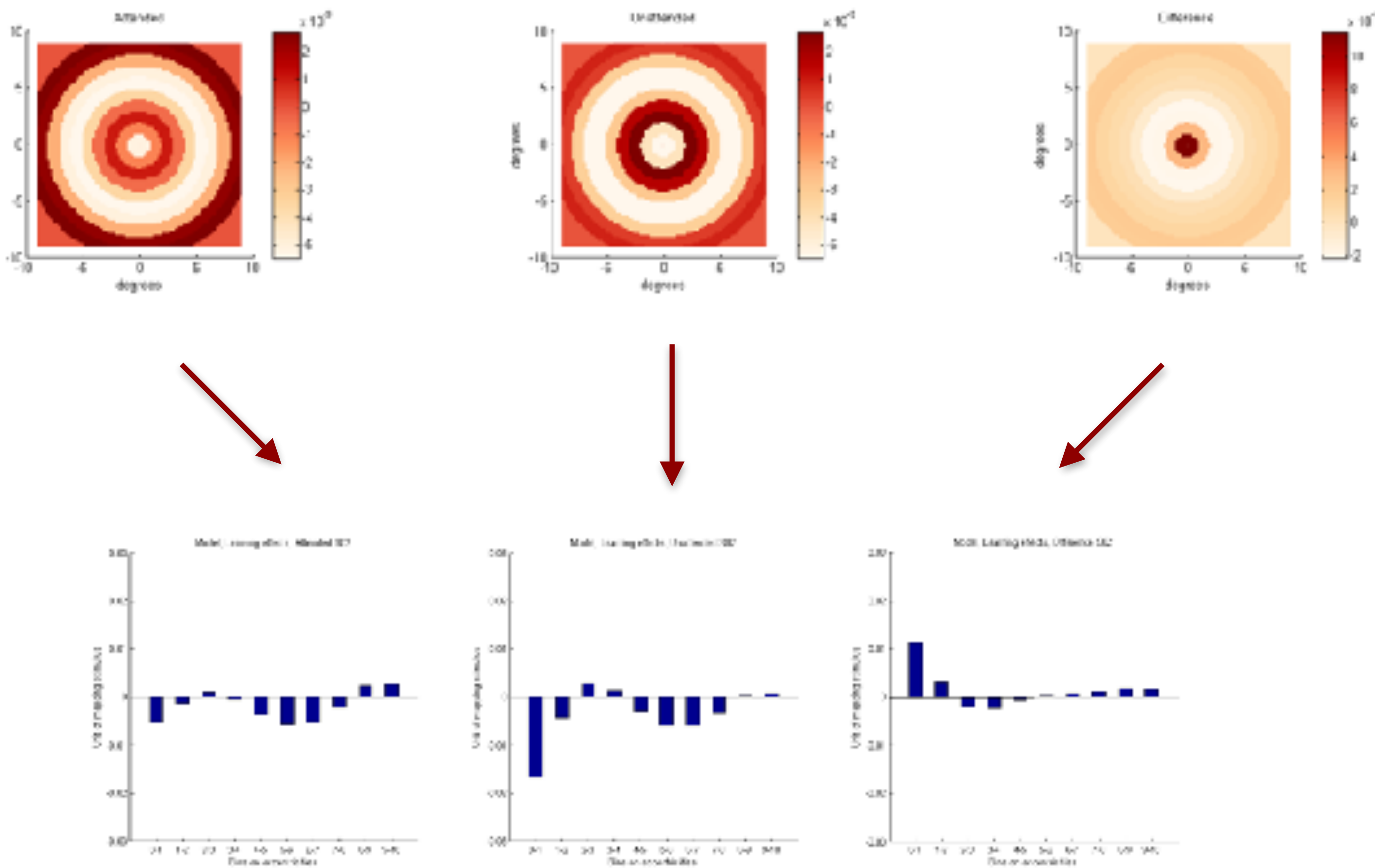


Figure:
Top plots: Average across pixel values. One ring every eccentricity.
Bottom plots: Same values but plotted in a bar plot.

Data Analysis:

Correlate brain and behavioural data

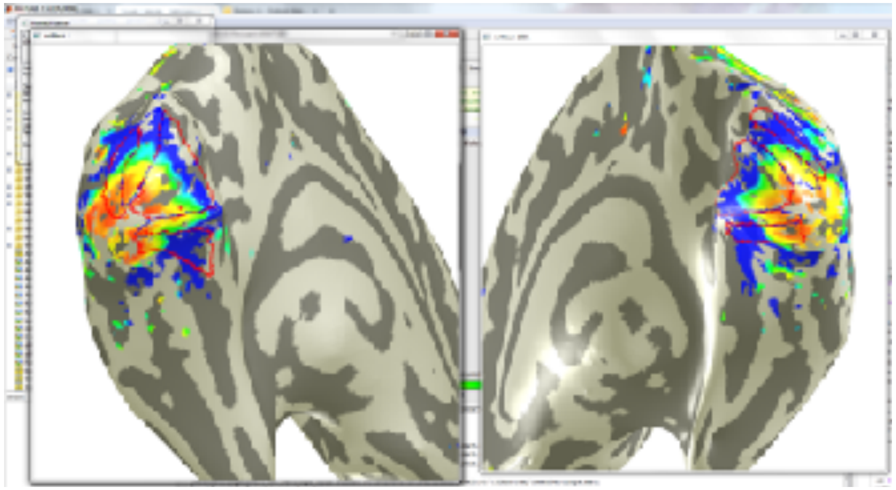
S03

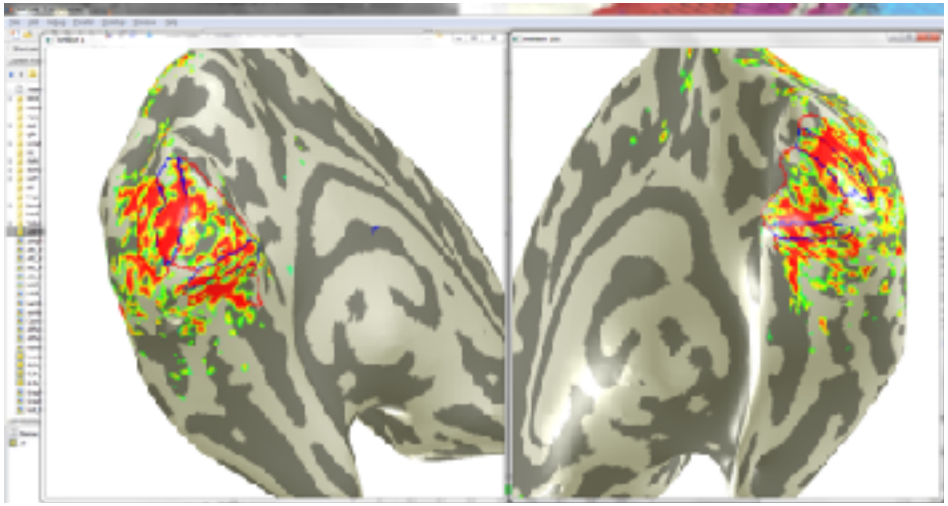
Pre-Training

Data plotted on the inflated brain
(T1 space)

Data Analysis:

Figure 1. Eccentricity maps





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Data Analysis:

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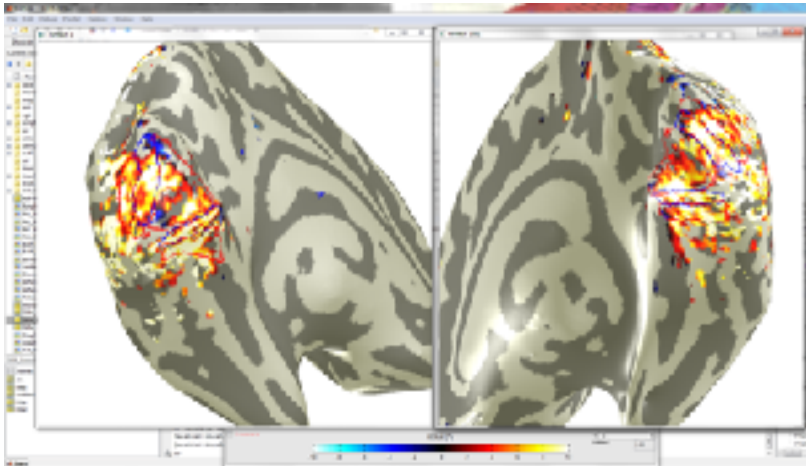


Figure 2. T-values from a GLM with contrast for the attended condition

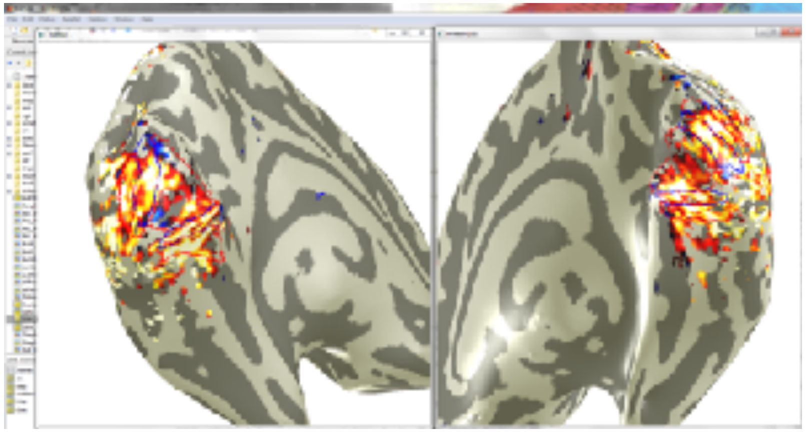


Figure 3. T-values from a GLM with contrast for the unattended condition

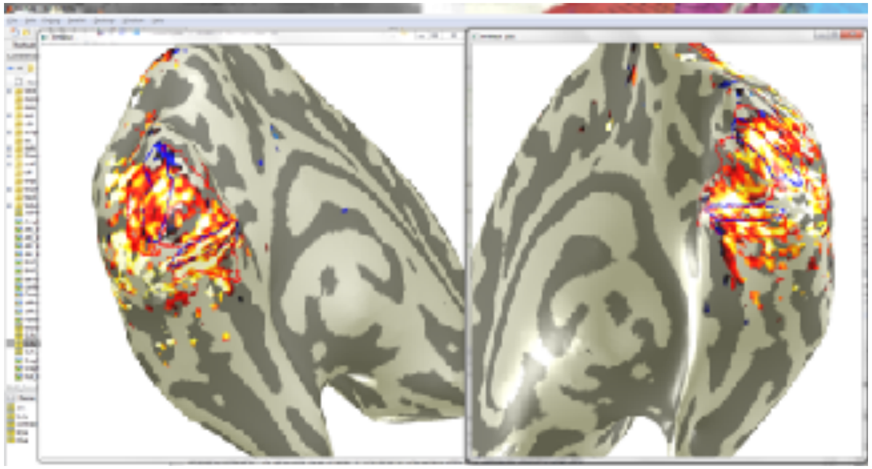
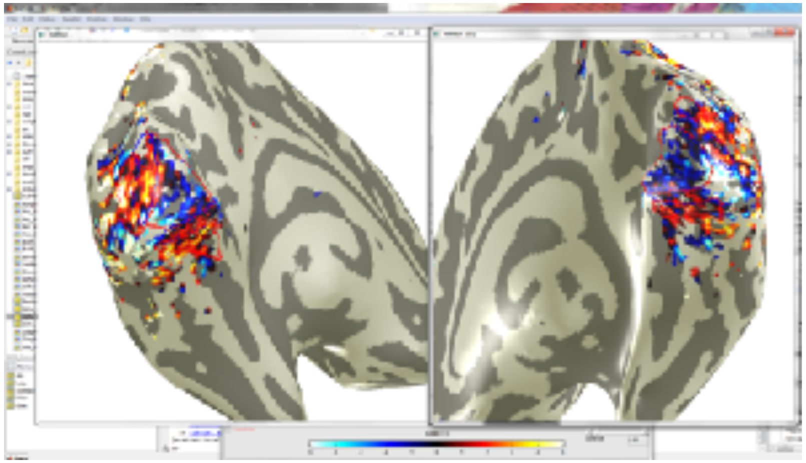


Figure 4. T-values from a GLM with contrast attended minus unattended



Data Analysis:

Pre-Training, S03

Voxels selected based on pPRF analysis

Figure 1

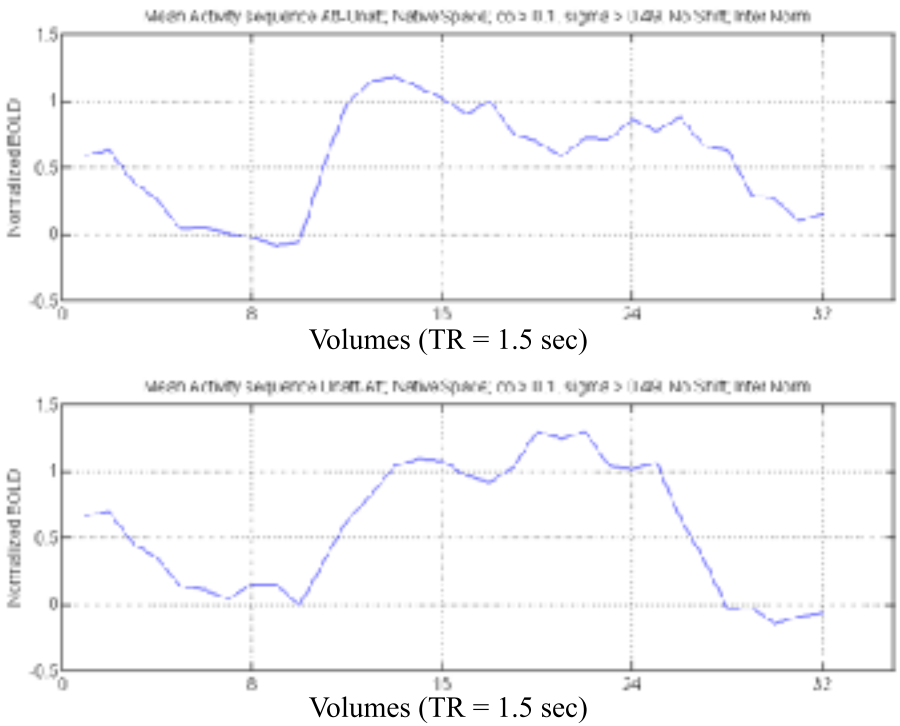


Figure 2

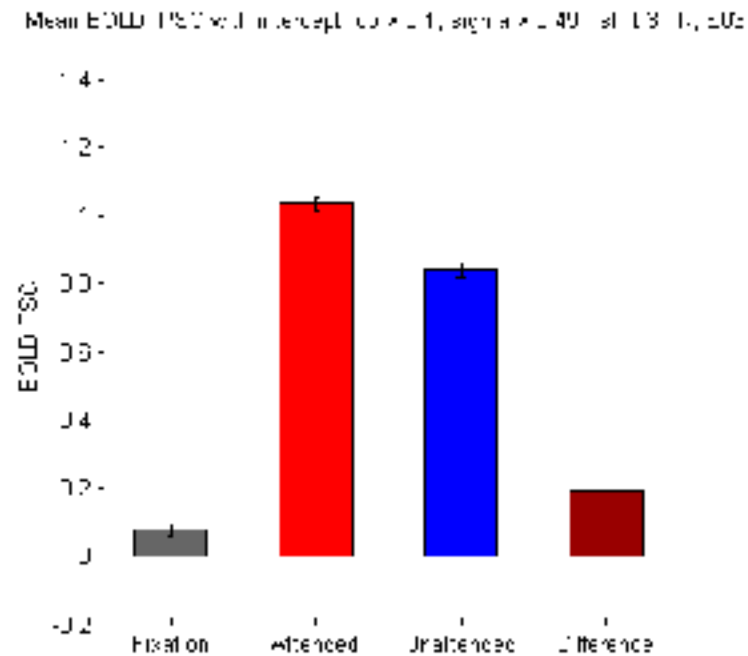


Figure 1. Mean BOLD. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter. The top row shows the sequence of blocks F-A-U-F while the bottom row shows the sequence F-U-A-F.

Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Pre-Training, S03

Voxels selected based on GLM/ stimulus-driven activity

Figure 1

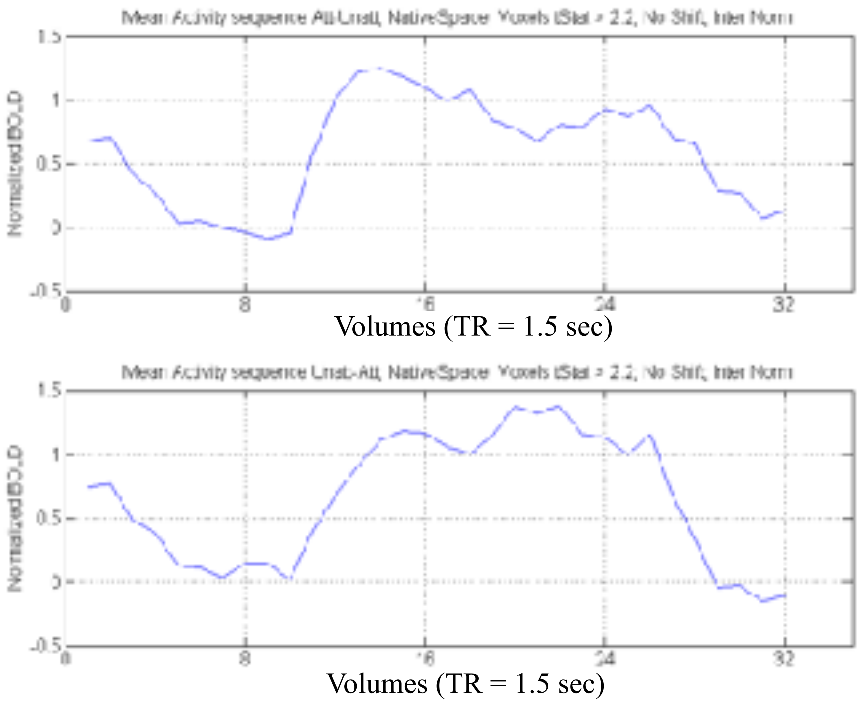


Figure 2

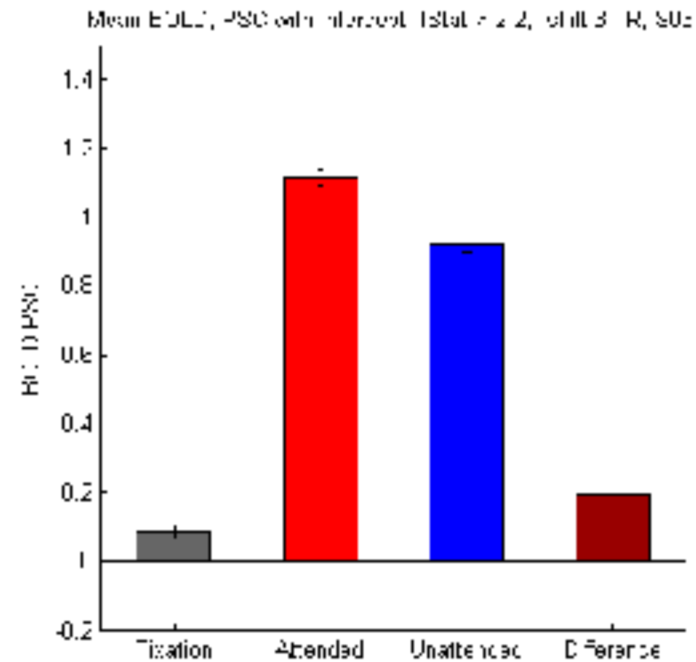


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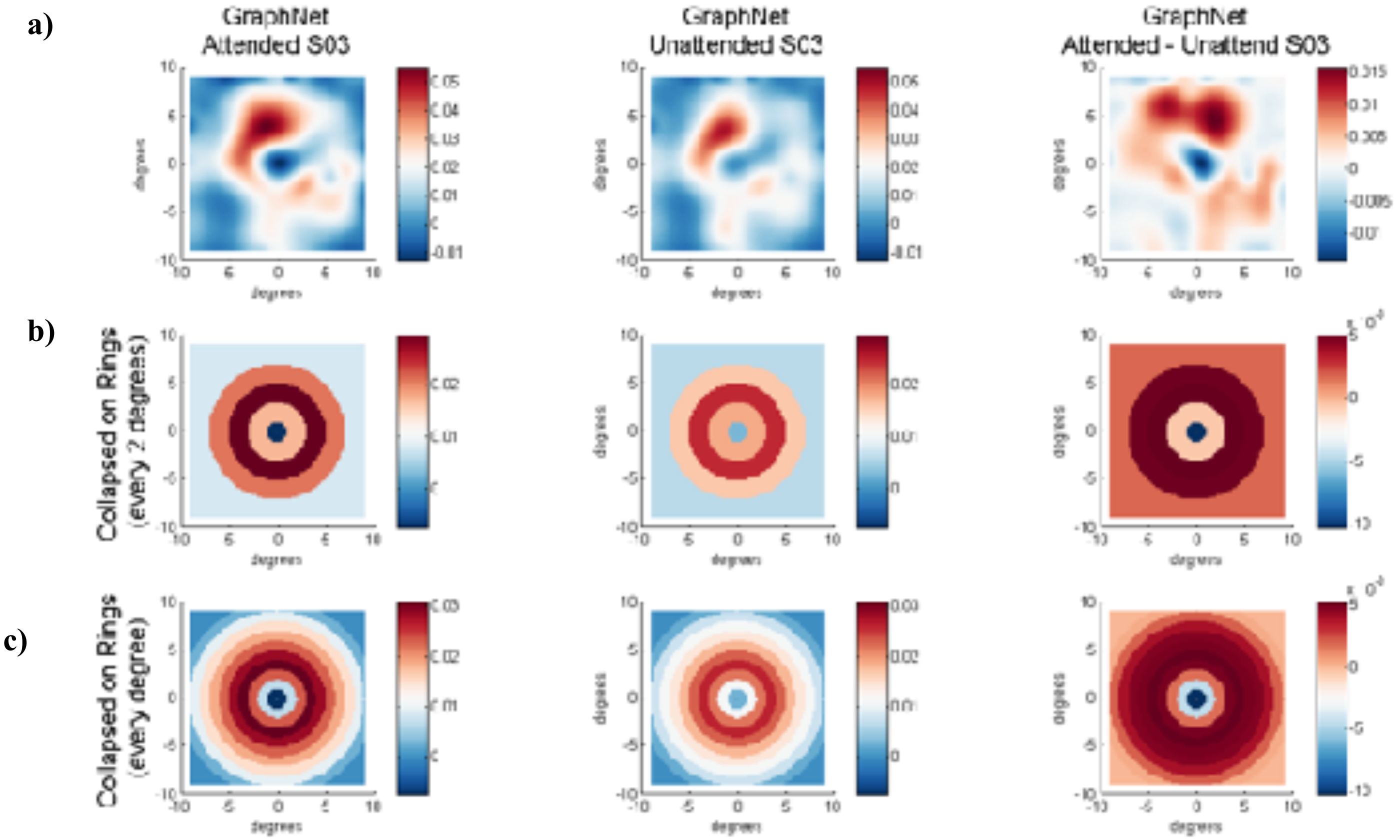
Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Pre-Training S03



a) GraphRidge model. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter **b)** Average across pixel values. Ring size matches the size of the presented stimulus **c)** Average across pixel values. Ring depicts eccentricity values.

Data Analysis:

S03, Pre-Training, all V1 to V3

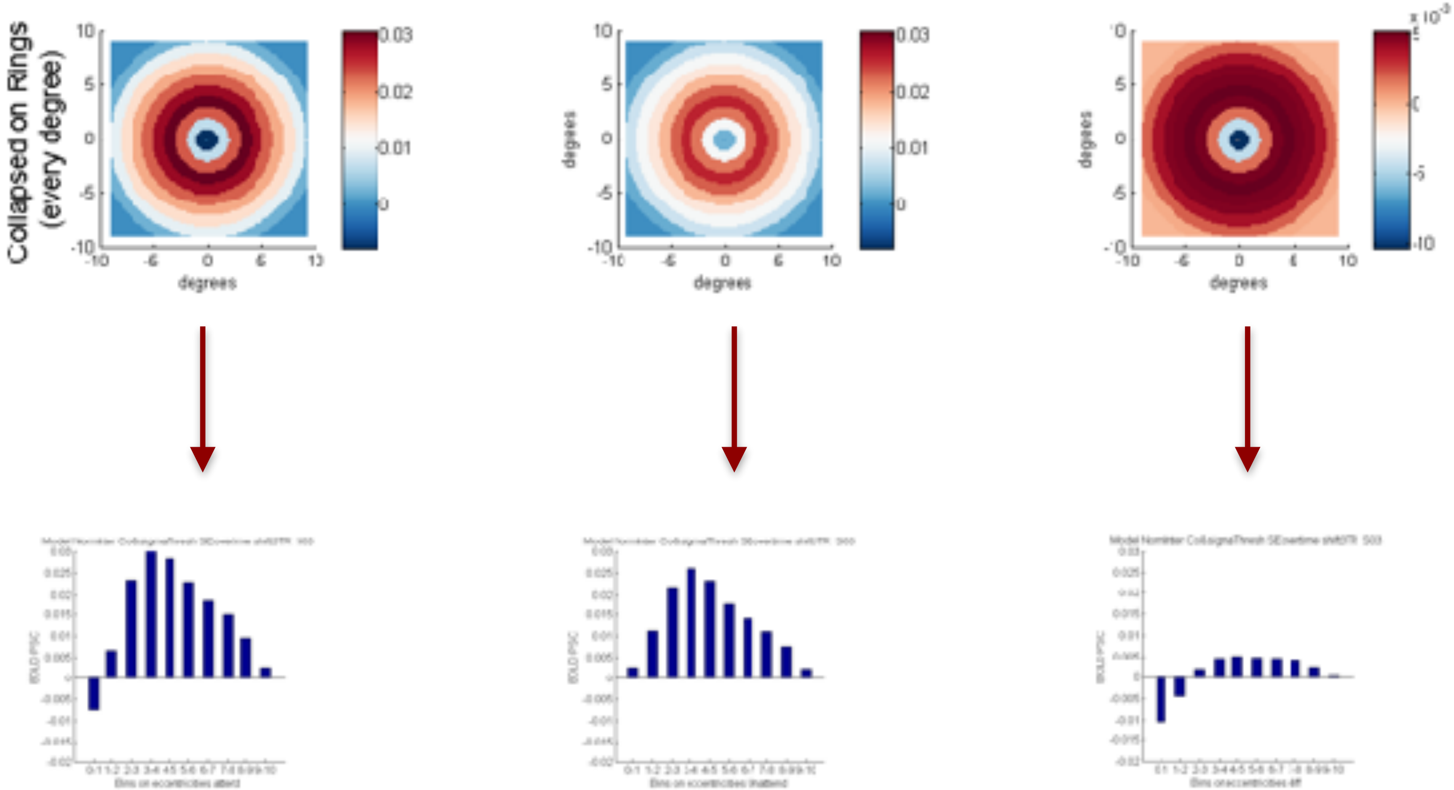
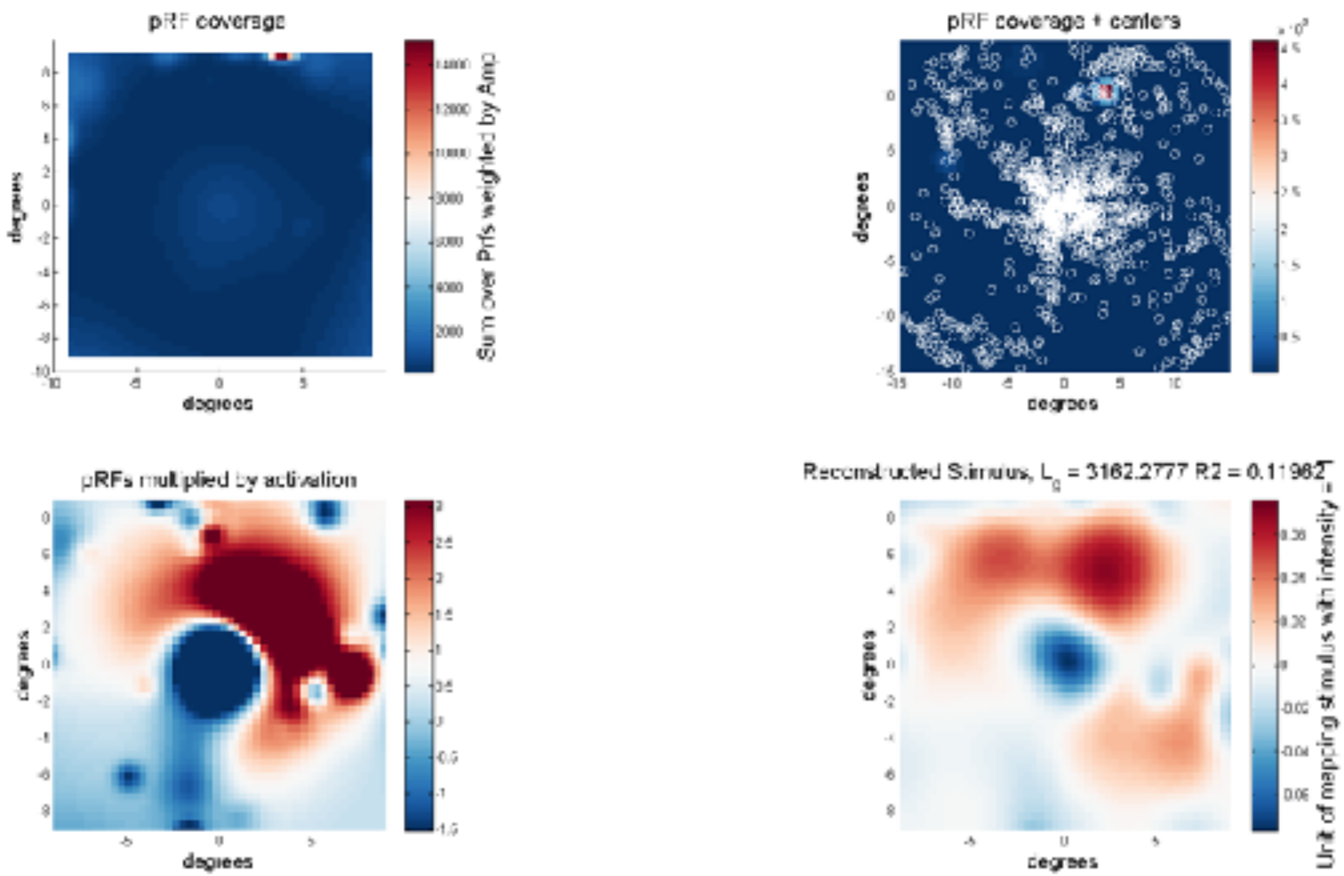


Figure:
Top plots: Average across pixel values. One ring every eccentricity.
Bottom plots: Same values but plotted in a bar plot.

Data Analysis:

S03, Pre-Training, all V1 to V3

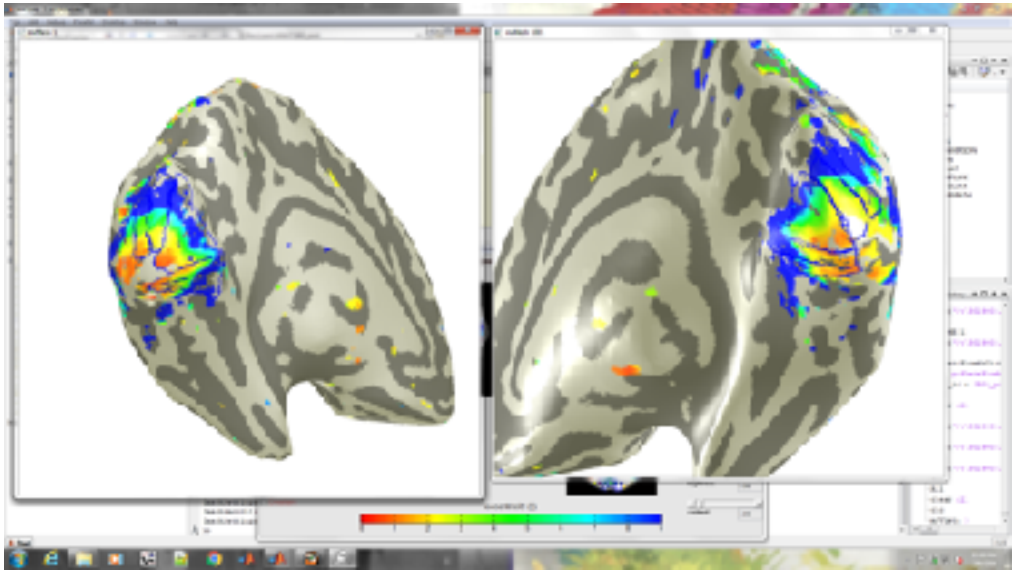


Post-Training

Data plotted on the inflated brain (T1 space)

Data Analysis:

Figure 1. Eccentricity maps



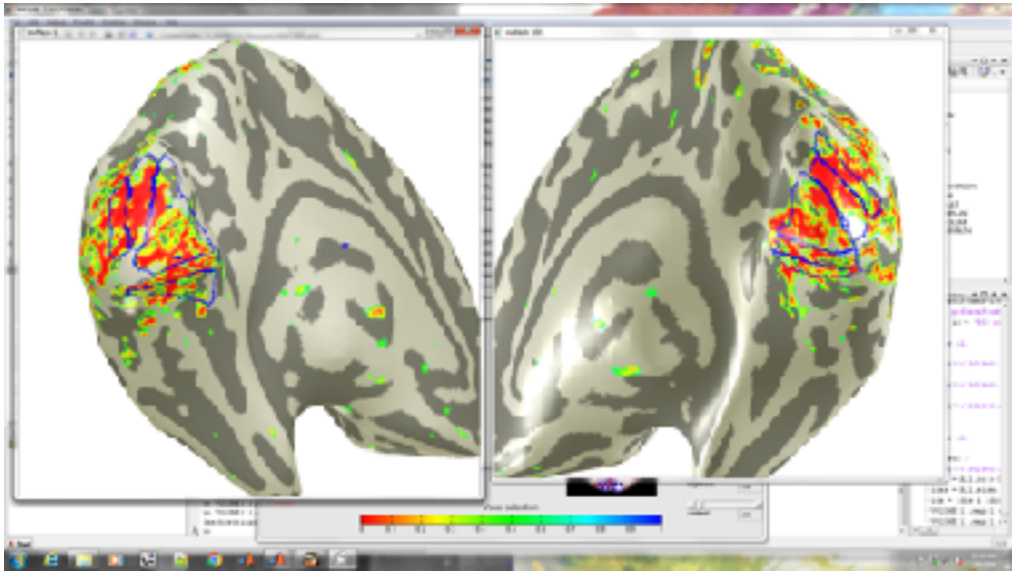


Figure 2. The map shows voxels' selection used for the Graphridge model. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance (voxels without color but within the drawn ROIs) and 2) pRF is at least 0.5 degrees VA in diameter (green voxels).

Data Analysis:

Figure 1. T-values from a GLM with contrast STIM_ON

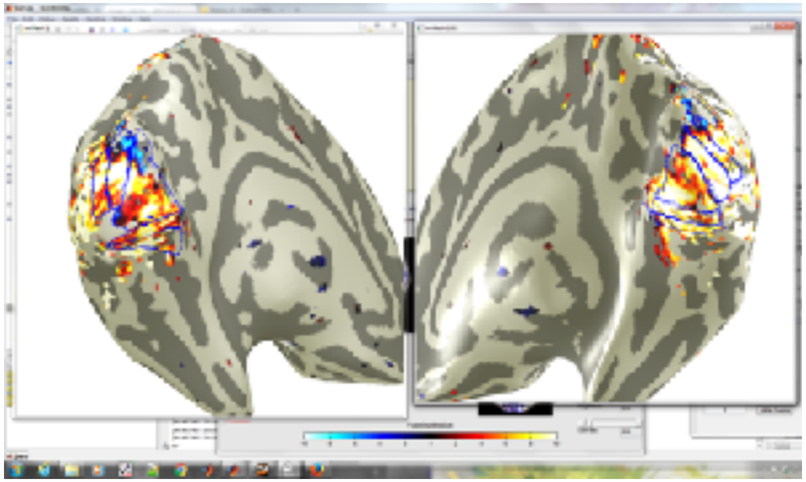


Figure 2. T-values from a GLM with contrast for the attended condition

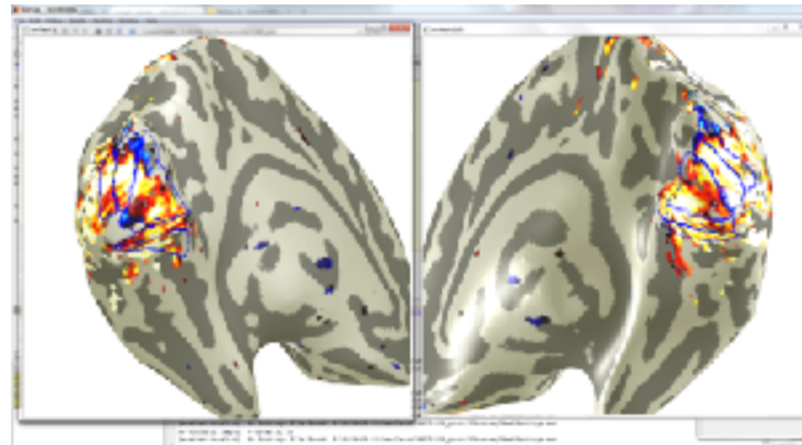


Figure 3. T-values from a GLM with contrast for the unattended condition

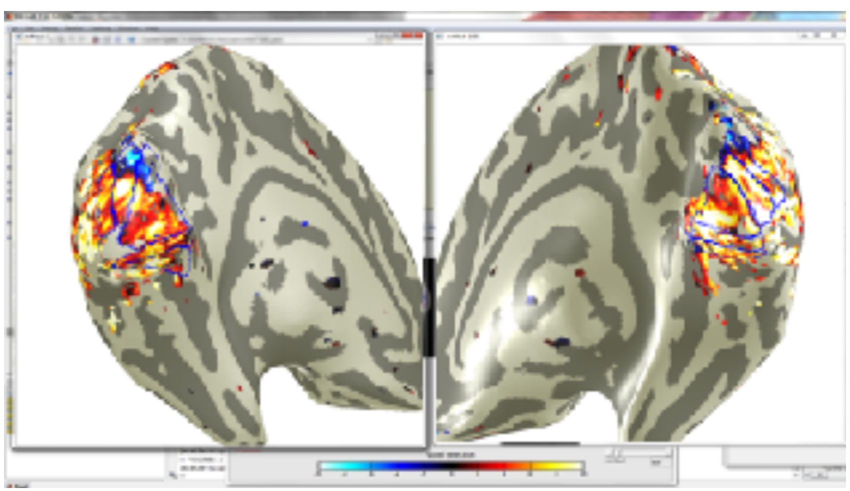
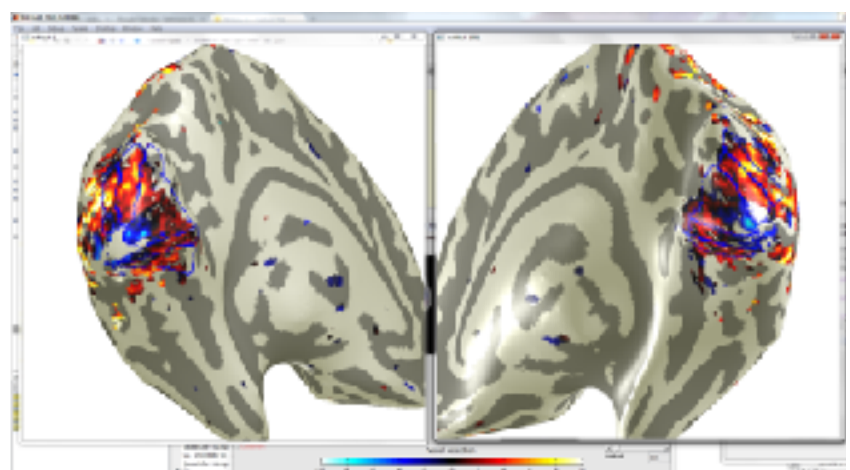


Figure 4. T-values from a GLM with contrast attended minus unattended



Data Analysis:

Pre-Training, S03

Voxels selected based on pRF analysis

Figure 1

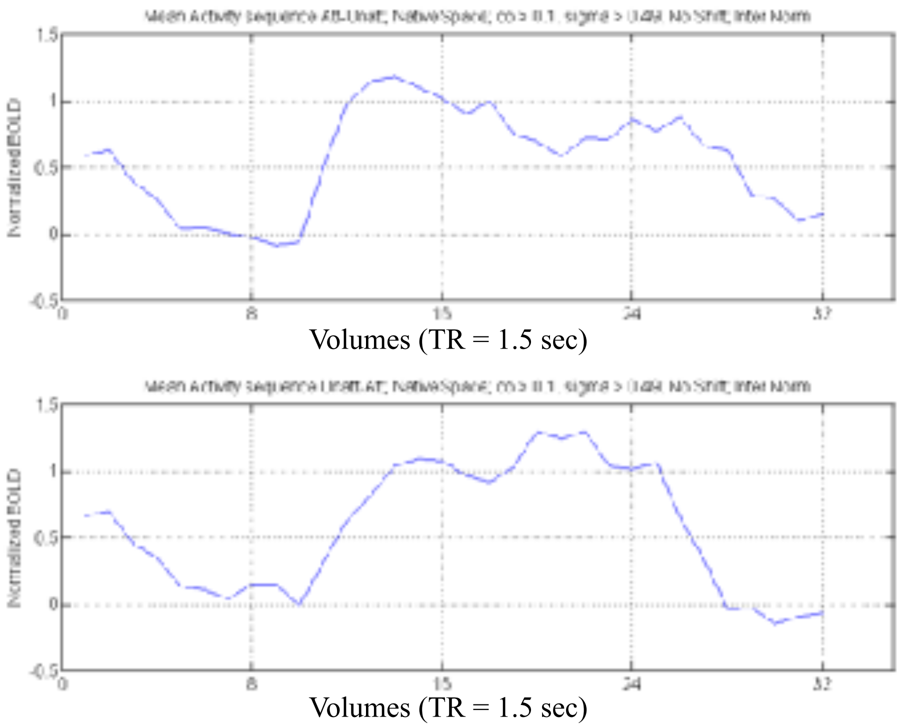


Figure 1. Mean BOLD. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter. The top row shows the sequence of blocks F-A-U-F while the bottom row shows the sequence F-U-A-F.

Figure 2

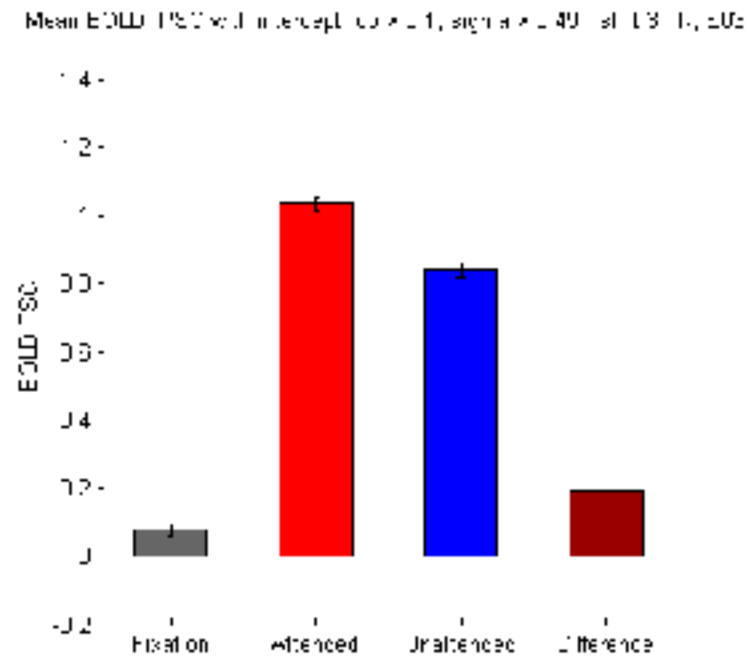


Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Pre-Training, S03

Voxels selected based on GLM/ stimulus-driven activity

Figure 1

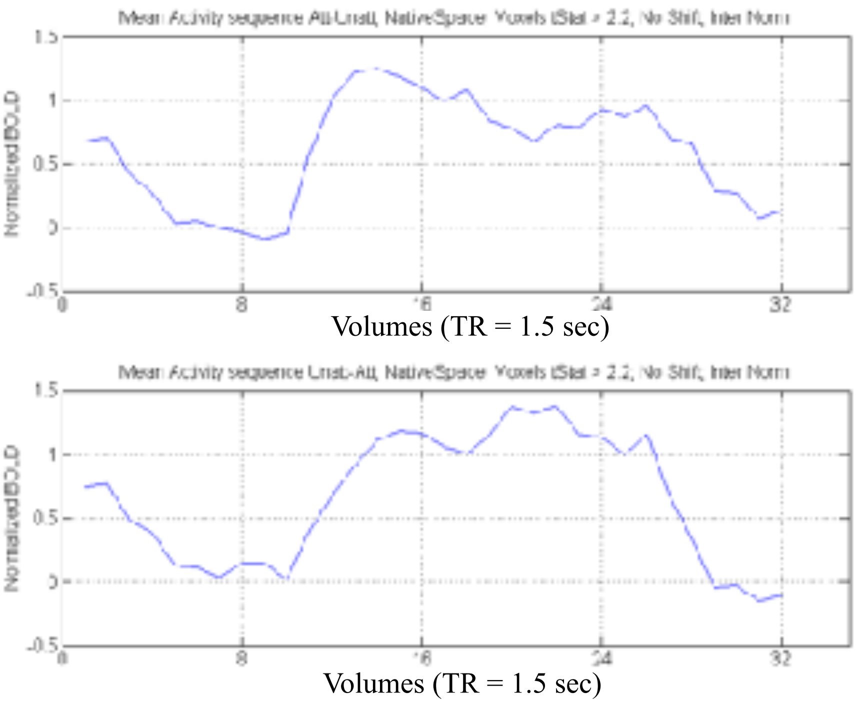


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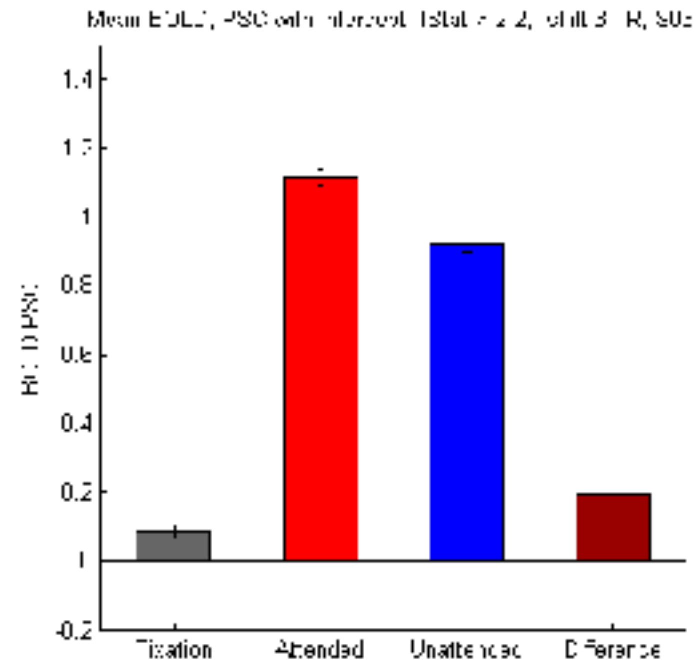
Figure 2



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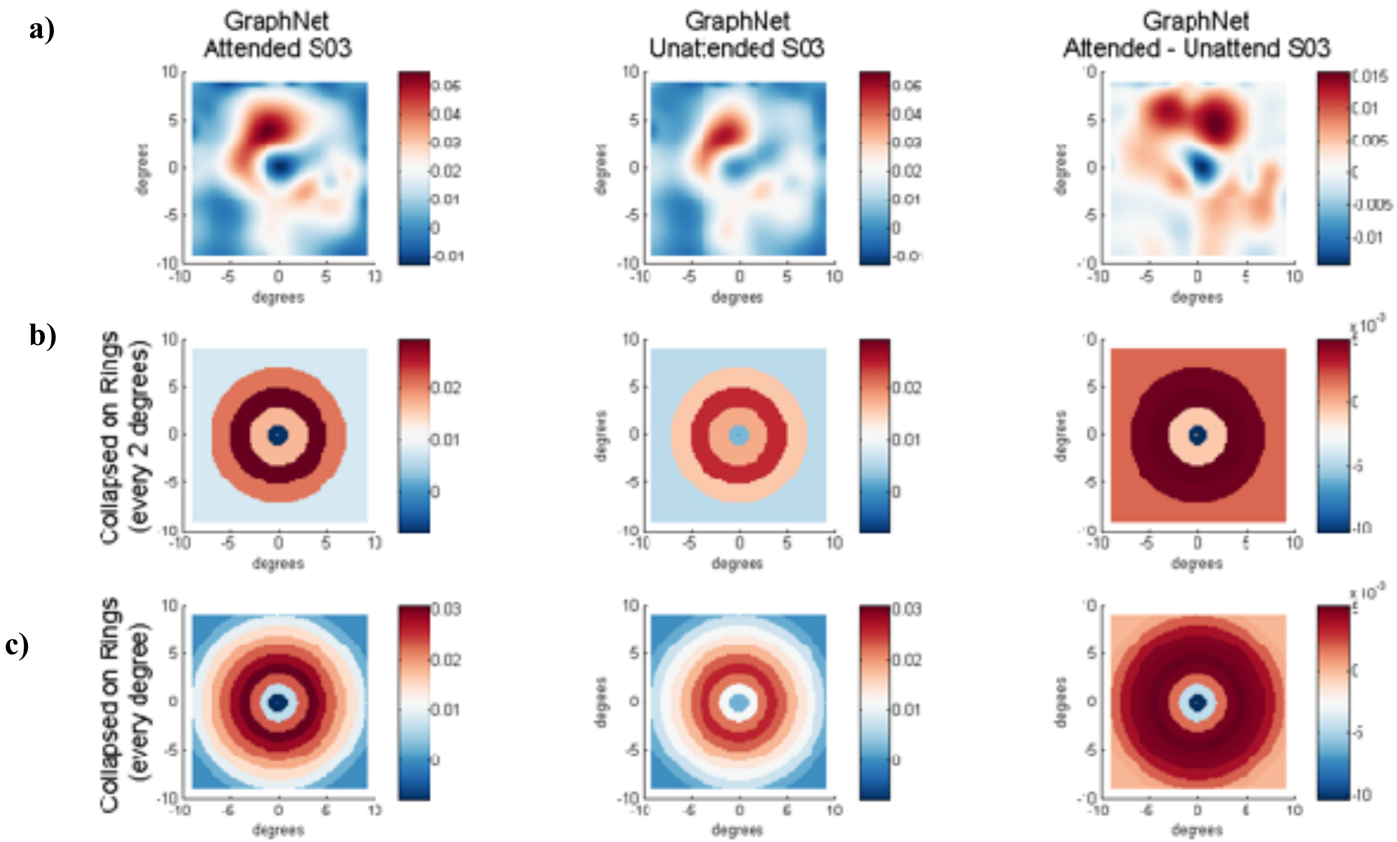
Data Analysis:

Pre-Training S03



a) GraphRidge model. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter **b)** Average across pixel values. Ring size matches the size of the presented stimulus **c)** Average across pixel values. Ring depicts eccentricity values.

Data Analysis:

S03, Pre-Training, all V1 to V3

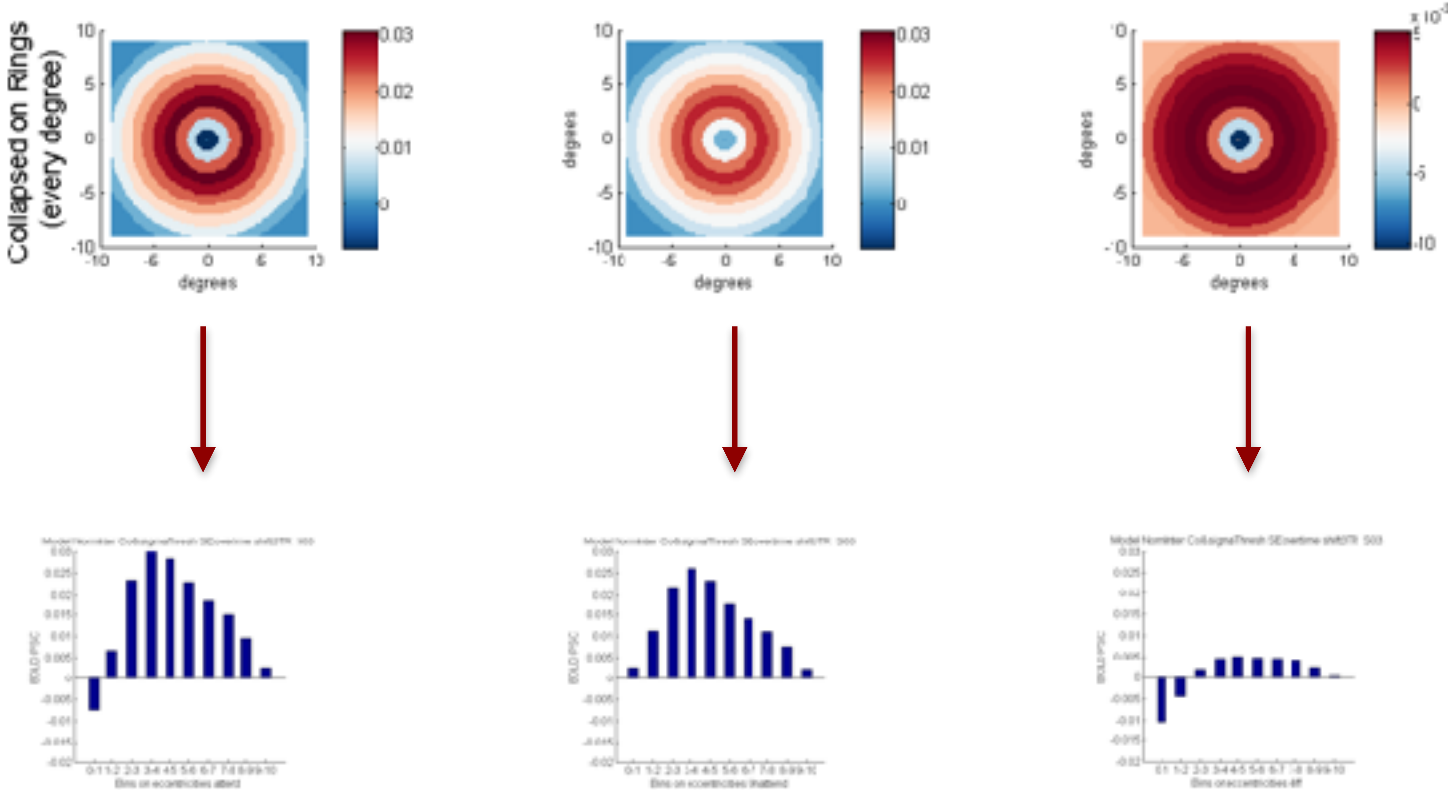
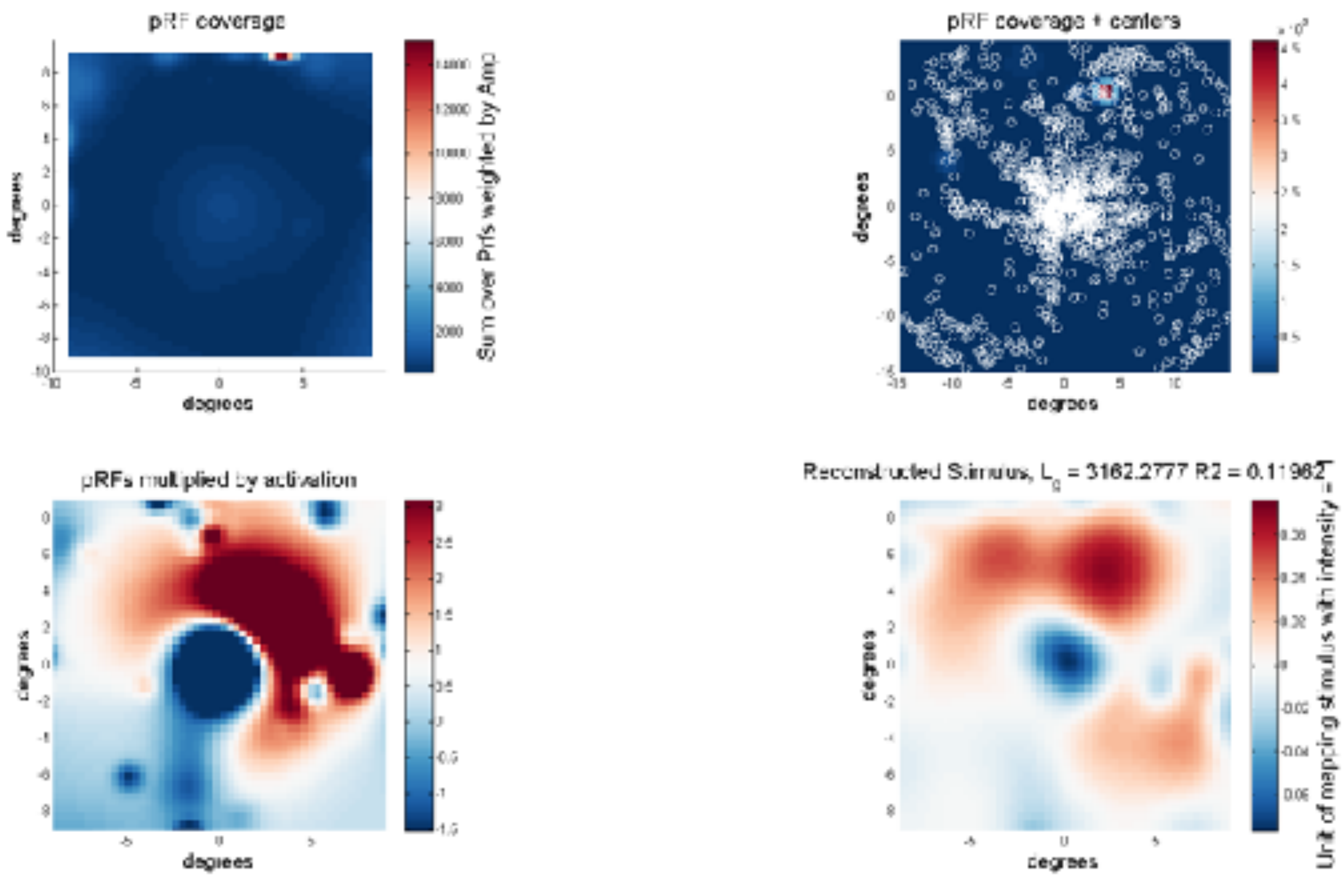


Figure:
Top plots: Average across pixel values. One ring every eccentricity.
Bottom plots: Same values but plotted in a bar plot.

Data Analysis:

S03, Pre-Training, all V1 to V3



Data Analysis:

Post-Training, S03

Figure 1

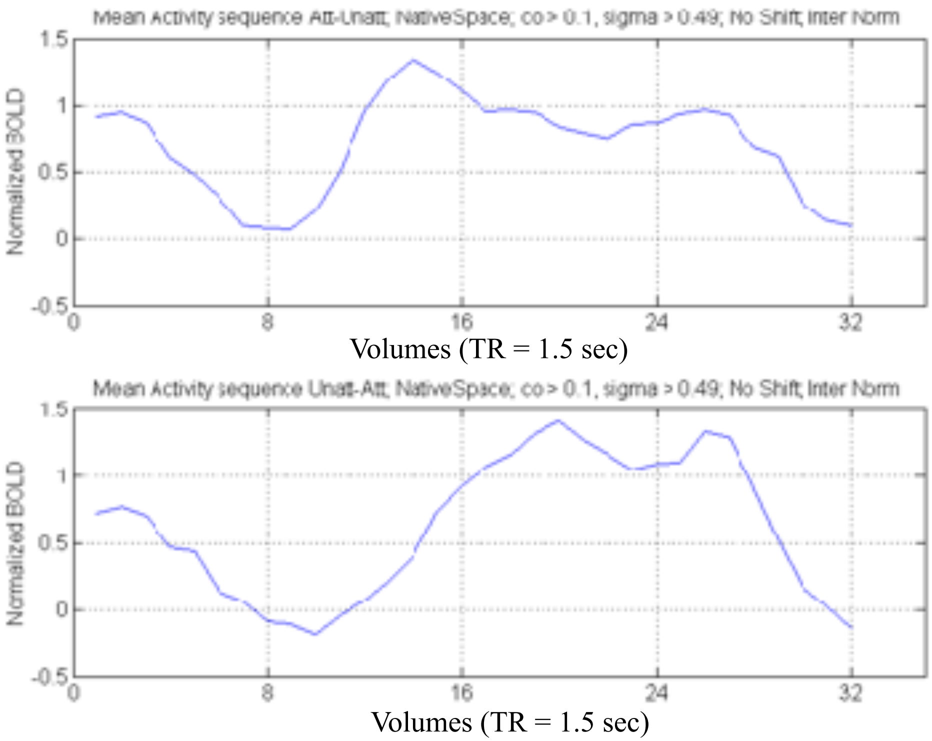


Figure 1. Mean BOLD. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter. The top row shows the sequence of blocks F-A-U-F while the bottom row shows the sequence F-U-A-F.

Figure 2

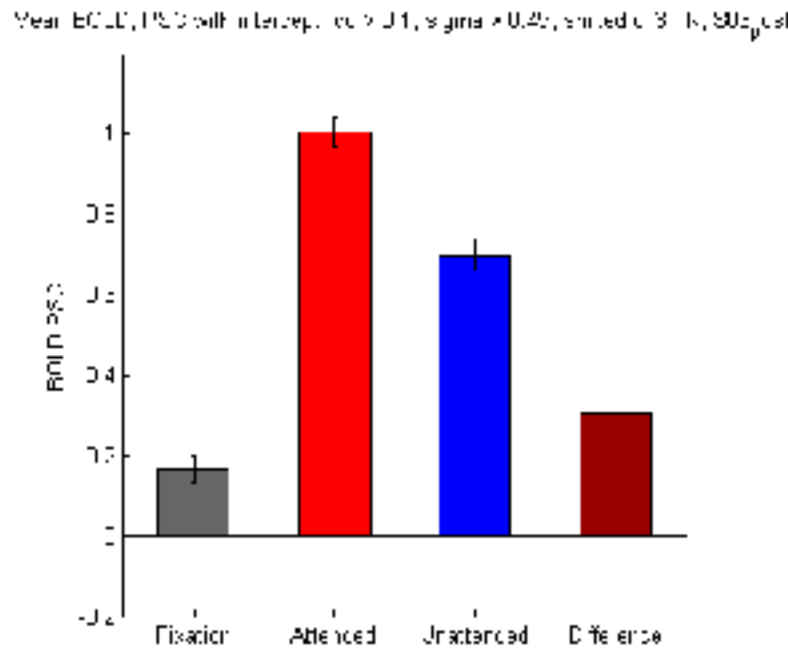


Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Pre-Training, S03

Figure 1

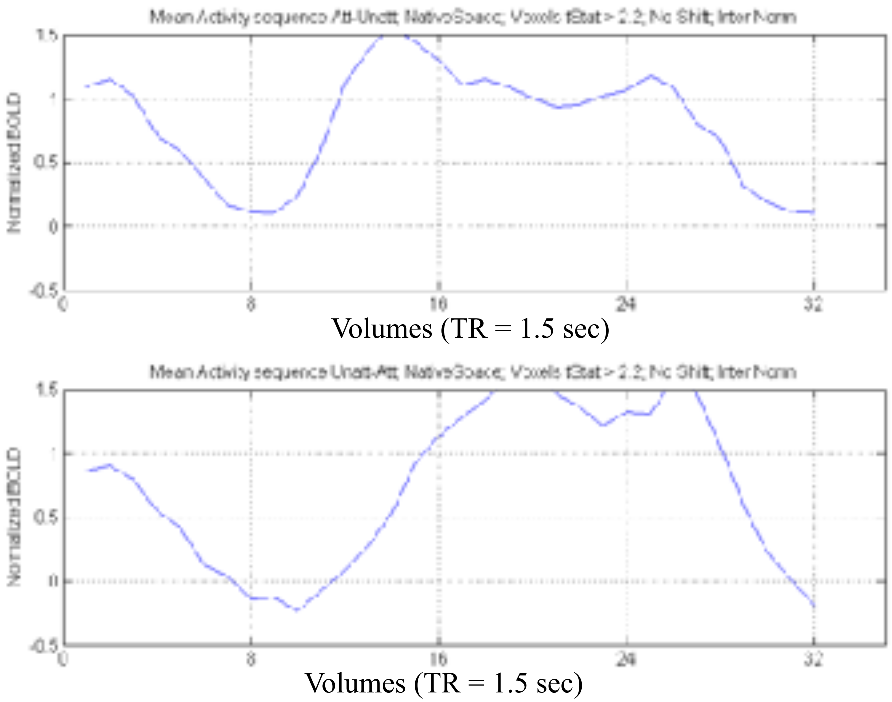


Figure 2

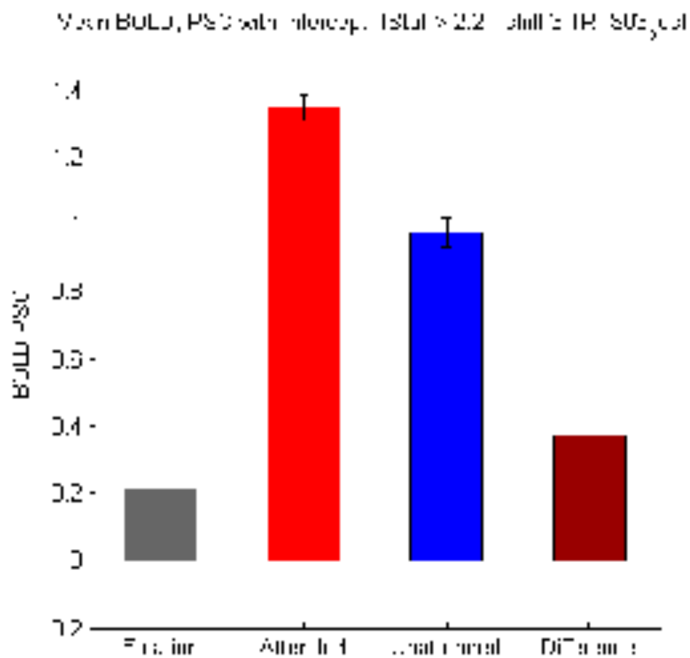


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Figure 2. Mean BOLD across the same set of voxels as Figure 1 for all conditions. Before averaging, the time-series was shifted by 3TR (4.5 seconds) to account for hemodynamic lag. The data was normalized by taking the intercept obtained in a standard GLM procedure on the raw BOLD time-series. SEM depicts the standard error of the mean across time.

Data Analysis:

Post-Training S03

a)

b)

c)

a) GraphRidge model. Voxels were selected based on the following criteria: 1) pRF model explains more then 10% variance and 2) pRF is at least 0.5 degrees VA in diameter **b)** Average across pixel values. Ring size matches the size of the presented stimulus **c)** Average across pixel values. Ring depicts eccentricity values.

Data Analysis:

Post-Training S03

Grid used here is 50 x 50 pixels

Figure 1

a)

b)

c)

d)

Figures: a) Sum over Gaussian receptive fields. The visual field extends up to 9 degrees. **b)** Sum over gaussian receptive fields. The visual field extends up to 15 degrees. **c)** Sum over Gaussians receptive fields multiplied by their activation during the main task. **d)** GraphRidge model.

Figure 1: Reconstructed stimulus during the **attended** condition.

Figure 2: Reconstructed stimulus during the **unattended** condition.

Data Analysis:

S03, Post-Training, all V1 to V3

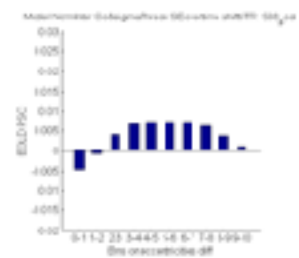

Figure:
Top plots: Average across pixel values. One ring every eccentricity.
Bottom plots: Same values but plotted in a bar plot.

Data Analysis:

S02, Post-Training, all V1 to V3

Learning effects

Data Analysis:

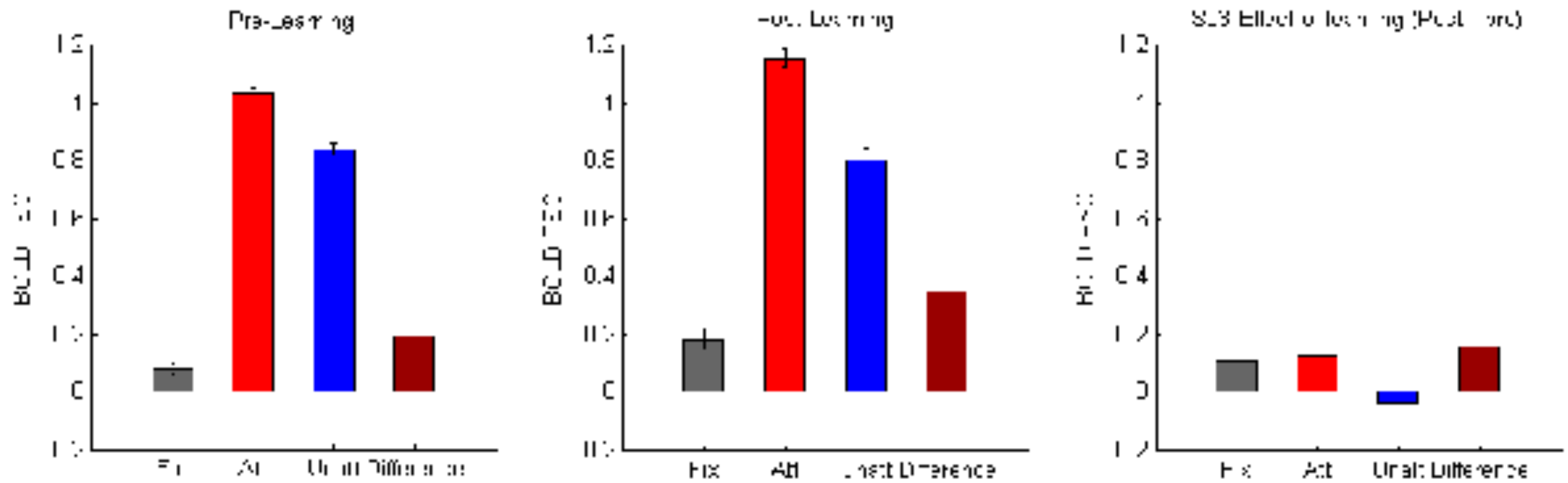

Figure. Mean BOLD of all voxels from V1, V2 and V3 for which the pRF model explained at least 10% variance and with a receptive field that extend at least for 0.5 degrees. Before averaging, the time-series had been shifted of 3TR (4.5 seconds) The normalisation of the time-series has been done using the intercept from a GLM performed over raw time-series. SEM has been computed over time on the averaged time-series across voxels.

Data Analysis:

Learning effects S03

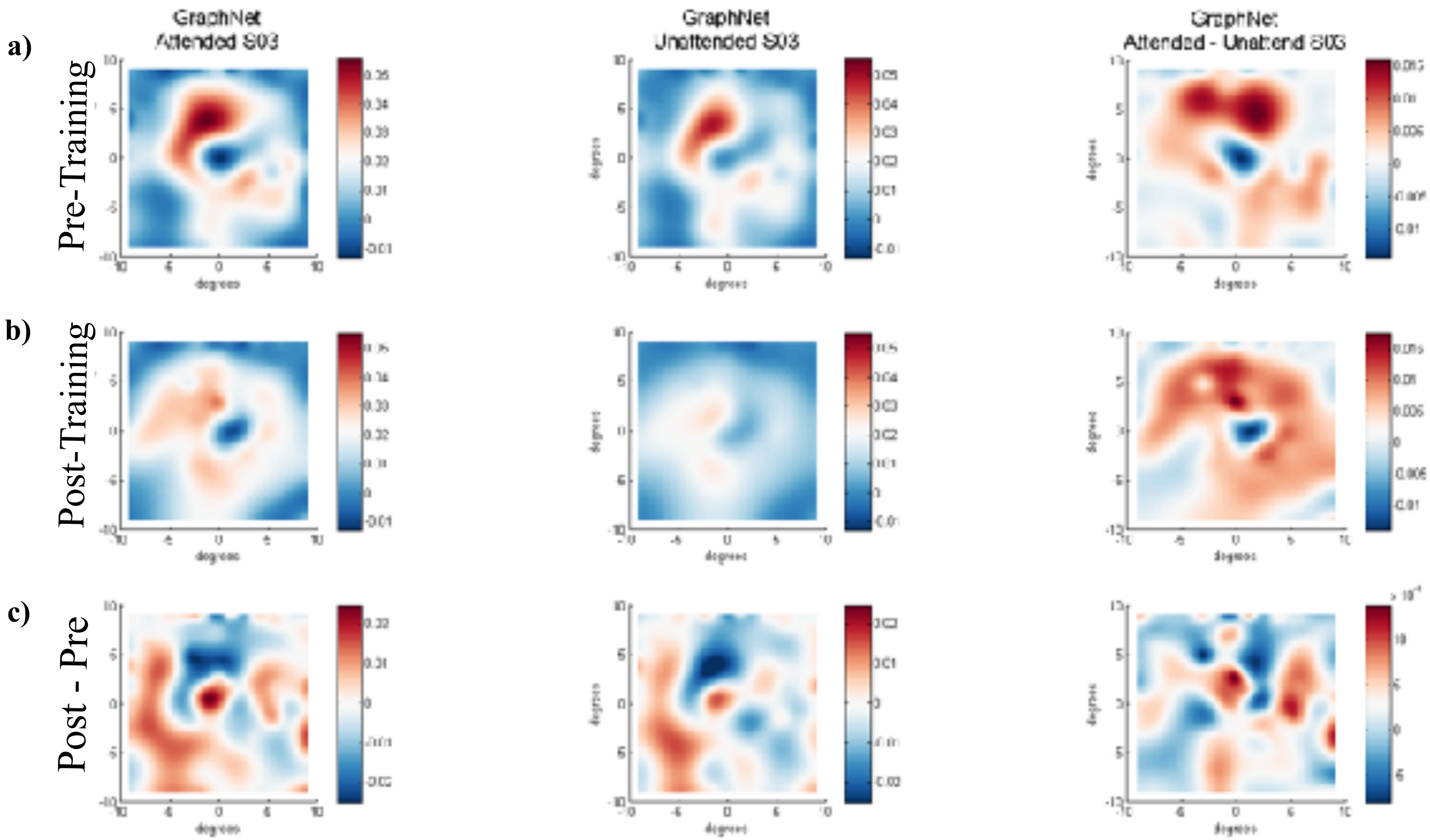

Figure. GraphRidge model: **a)** before training , **b)** after training, **c)** the plots have been created by subtracting pixel's values of post-learning reconstructed stimuli to those of the pre-learning stage. <u>However, as we did not use here the same value of lambda for all the reconstruction, the output might not be interpretable.</u>

Data Analysis:

S03, Post-Training, all V1 to V3

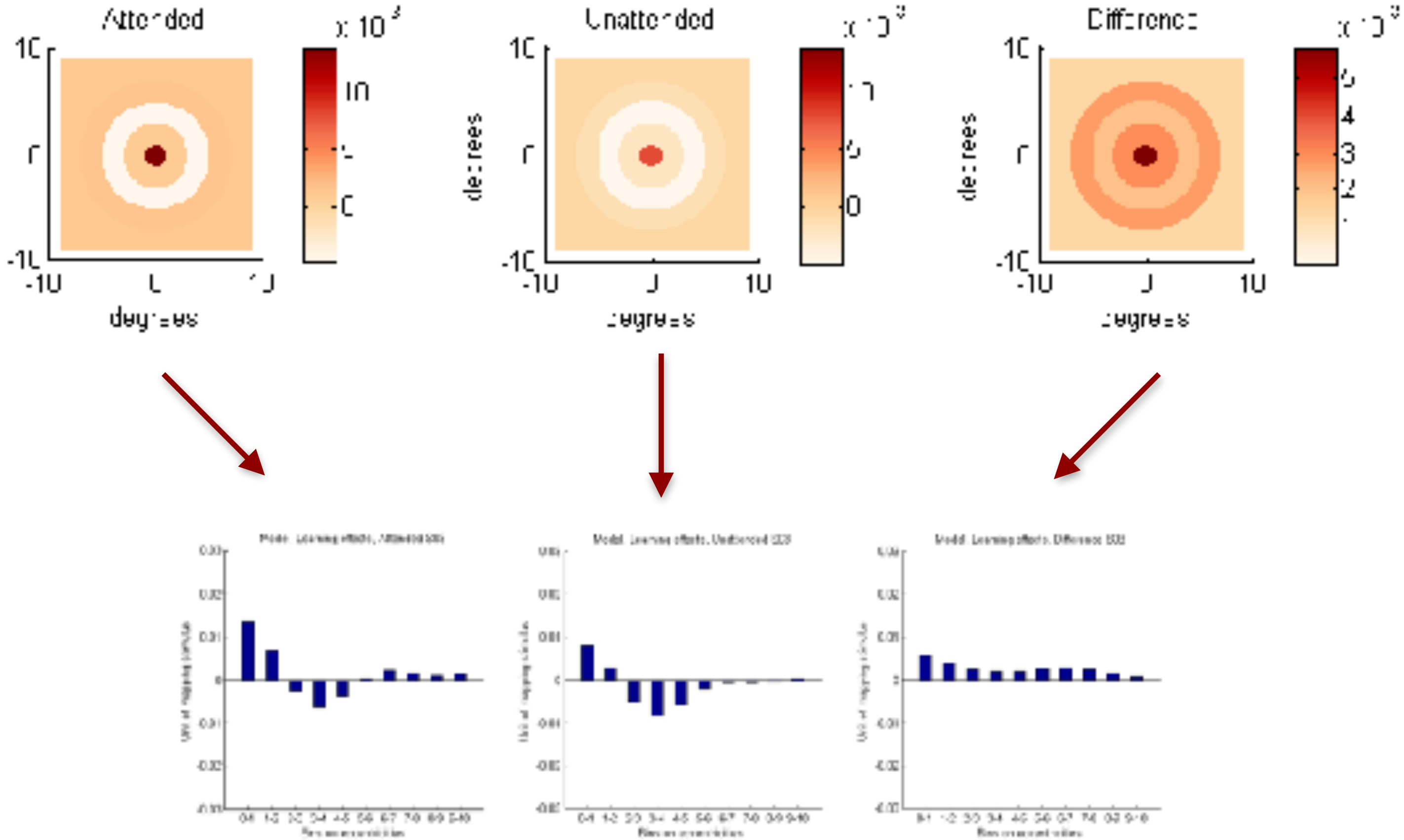

Figure:
Top plots: Average across pixel values. One ring every eccentricity.
Bottom plots: Same values but plotted in a bar plot.

Data Analysis:

Correlate brain and behavioral data

Details

Nr of subjects:

• 15 subjects needed (e.g. Jehee et al, J.Neurosci., 2012) . Scan 20 as we expect some dropout.

Lab usage:

Behavioral:

1h practice + 3h pre-thresholding + 10h training + 3h post-thresholding = 17 h each

7h * 20 subjects = **340 h**

fMRI:

3 h (2h fMRI + 1h setup) * session = 6h each

6h * 20 subjects = **120 h**

Quota:

(3gb default + 1.5 gb (multiband sequence)) * 2 hr + 8 gb for pRF analysis = 17gb each session

17gb * 20 * 2 = **680 gb**

Theoretical relevance

Better understanding of the neural underpinnings of perceptual learning

Reconciling current theories: training improves higher-level read out as well as lower-level stimulus representation via mechanisms of top-down attention

Understanding the mechanisms of low-level skill learning could ultimately help devise therapeutic interventions for patients

Open questions:

•Which ROI(s) shall we use as higher-level regions? Should we define them functionally (so for instance using pRF or GLM) or anatomically?

1st idea: whole-brain GLM with attention & learning as regressors. Then, some cluster analysis.

•If they are not retinotopic regions, which analysis shall we perform?

•If our intention is to show a learning that is spatially specific, do we really want to remove the 4th ring? It might lead to observe changes with learning on the whole stimulus as subjects seems to use information in the 3rd ring after learning.